Understanding Participation in a Long-Term Household Panel Study: Evidence from the UK

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Declarations

No part of this thesis has been submitted for another degree.

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Summary

Longitudinal surveys provide valuable data to analysts and policymakers as societal topics can be studied over time. Consistent survey participation is required and encouraged. However, nonresponse or panel attrition (cumulative and permanent nonresponse) can prevent this and therefore is a concern to survey methodologists. This is particularly problematic when nonrespondents are systematically different from respondents, thus biasing survey estimates, potentially resulting in inaccurate inferences about the population. Understanding and improving survey participation has been, is and will continue to be a challenge survey methodologists face due to the dynamic nature of panel surveys (births, deaths, and migration) and how the survey landscape changes over time (e.g., mode shifts and technological advancements) so this thesis aims to contribute to the continued and changing understanding.

This thesis uses data from *Understanding Society*: The UK Household Longitudinal Study (UKHLS), a household panel survey that follows sample members and aims to represent the UK population. Each substantive chapter uses a different component of the Study to examine aspects of survey participation. The thesis starts by introducing the relevant background of survey participation and nonresponse in longitudinal surveys. Chapter 1 uses data from the British Household Panel Survey sample (UKHLS' predecessor study that was incorporated into the ongoing survey) to identify loyal sample members and examine response patterns over a thirty-year period. Chapter 2 considers the impact of the COVID-19 pandemic on survey dataset quality, in terms of likely nonresponse biases, by comparing survey data quality in the pre-pandemic mixed-mode UKHLS main survey with the primarily web-based UKHLS COVID-19 Study. Chapter 3 examines youth interview response behaviour to gauge whether it can predict early adult response behaviour in the UKHLS. The thesis concludes by

discussing how the findings contribute to the literature on survey participation and inform survey practices in the future.

Contents

List of Tables

List of Figures

Introduction

Longitudinal studies enable researchers to study societal trends over time. This thesis focuses on one type of longitudinal study, household (HH) panel surveys. HH Panel surveys typically sample the general population, and aim to interview every person in the household at various time points (waves), covering a multitude of topics such as health, income and family dynamics (Lynn, 2009a). Unlike repeated measures cross-sectional studies, where the same questions are asked of different people over time, data from panel surveys enables the analysis of changes between and within individuals (Lynn, 2009a). Consequently, it is important to ensure all eligible sample members respond at all survey waves so valid inferences can be made about the study population (Groves et al., 2009).

However, non-participation by survey sample members inevitably occurs. In the first instance, sample members may become ineligible, due to moving out of the scope of the survey, physical or mental incapacitation, or death. Alternatively, they may not respond to the survey. Conceptually, the nonresponse process can be categorised into three conditional parts: 1) non-location; 2) non-contact; and 3) refusal (Lepkowski & Couper, 2002). Sample members first have to be located, using their contact details (e.g., residential address, phone number, email address). Then, they need to be contacted, through an interviewer, or by sending mailings with the interview details, (sometimes it is not possible to know whether a sample member has been located until they have been contacted, so these first two categories may be combined for convenience). Next, once contact has been established, the sample member has the choice to respond or refuse. Understanding survey participation is important because response rates have been declining over many years (de Leeuw & de Heer, 2002; Luiten et al., 2020), and some long running panel surveys can expect to lose a considerable amount of the original sample (Burton et al., 2004). This negatively impacts on survey dataset quality. Reductions in sample size lead to less precise survey estimates. Additionally, if nonrespondents are systematically different from respondents and involved characteristics are correlated with survey responses, survey estimates can deviate from study population values (nonresponse biases) (Groves et al., 2009; Lynn, 2018; Uhrig, 2008).

Nonresponse in panel surveys is even more complex because sample members are asked to participate on multiple occasions. As such, nonresponse is not a simple dichotomy, but rather a series of dichotomies that can be viewed as a pattern. One common pattern is for sample members to drop out of the survey completely, causing the permanent and cumulative loss of sample members (known as panel attrition). Moreover, response rates may also differ across surveys waves, for example, it is known that nonresponse is highest in the first few waves of a survey (Uhrig, 2008). In addition, changes such as births, deaths and migration must be accounted for, to ensure the sample continues to reflect the changing study population. It should be noted that since panel surveys are reliant on repeatedly interviewing the same individuals, simply replacing those who have attrited with new sample members is not a useful solution to these issues (Lynn, 2018).

There is a wealth of research surrounding survey participation. Much of this is concerned with identifying the types of sample members that participate (and those who do not) in the survey and the reasons why (see Groves et al. (1992); Uhrig (2008); Watson and Wooden (2009) for reviews). Understanding these topics is important because it enables strategies to encourage participation and reduce attrition to be implemented. Moreover, these strategies are also implemented with the aim of ensuring that the respondent dataset reflects the study population, which minimises nonresponse biases. Such strategies are known as bias prevention techniques (Laurie & Lynn, 2009; Lynn, 2017; Singer & Ye, 2013; Watson &

Wooden, 2009). Techniques are also available to reduce remaining biases post-data collection, such as nonresponse weighting and imputation of missing survey responses (bias adjustment techniques: see Carpenter & Kenward, 2012; Kenward & Carpenter, 2007; Lynn & Kaminska, 2010; Valliant, Dever, & Kreuter, 2018). These are again informed by knowledge of the causes of survey participation. It should be noted that their effectiveness is increased by successful implementation of bias prevention techniques i.e., by a respondent dataset that reflects the study population (Moore et al., forthcoming; Schouten et al., 2016).

Concerning the causes of survey participation, Groves et al. (1992) contend that understanding the decision to participate should integrate factors that can be observed, such as survey design features and respondent characteristics, and factors that are less observable, such as societal-level factors. Societal-level factors refer to global characteristics that influence the decision to participate, including social cohesion and public attitudes towards the survey industry (Groves et al., 1992). These factors are related to the aforementioned global decline in survey participation (de Leeuw & de Heer, 2002; Luiten et al., 2020) and the way in which survey participation can differ over time and by country (Behr et al., 2005; Luiten et al., 2020; Olson & Witt, 2011), but are difficult to measure. Given this, the research in this thesis will focus on the factors that can be observed.

Survey design features should aim to reduce attrition and ensure that respondents reflect the study population but can also be dependent on the availability of financial and time resources. They can include mailings (e.g., interview reminders, between-wave communication), tracking sample members that move, the number of and timing of calls, respondent incentives, the interviewer (e.g., how many interviews are used, how their time is managed and their characteristics including experience level) and the interview experience (e.g., interview length, the content, its ease, survey mode) (Burton et al., 2004; Frankel & Hillygus, 2014; Laurie & Lynn, 2009). These features are typically standardised so the survey is the same for sample members, but it has been shown that implementing some features in a targeted manner can be beneficial, especially with regard to ensuring the respondent dataset reflects the study population (i.e., bias prevention: Groves (2006); Groves et al. (2009); Peytchev et al. (2010); Singer and Ye (2013)). However, to employ such techniques effectively research is required to understand the causes of survey participation in the survey in question.

A key topic for understanding survey participation is determining its correlates. This informs on (likely) nonresponse biases, enables identification of sub-groups that are less likely to participate so that they can be targeted by bias prevention techniques, and enables identification of auxiliary covariates that should be included in models underlying bias adjustments. Concerning such correlates, characteristics that are associated with residential stability and community attachment increase the likelihood of being contacted. These include being a homeowner, older and/or married, having a high income, children in the household, and living in accommodation with its own entrance (Behr et al., 2005; Burton et al., 2004; Gerry & Papadopoulos, 2015; Uhrig, 2008; Watson & Wooden, 2009). Conversely, moving address reduces the likelihood of being contacted, and also tends to be associated with significant life events that survey designers want to quantify, such as new or loss of employment, having a child, and change of marital status (Müller & Castiglioni, 2015; Voorpostel & Lipps, 2011).

Moreover, characteristics associated with availability, such as being retired or a stay-at-home parent, are related to whether a sample member has the spare time to participate in the survey.

In contrast, characteristics associated with the lack of availability, such as being employed or a student, having children in the household, working untraditional hours (e.g., working nights or weekends, or irregular hours), or being in a single person household decrease the likelihood of response (Uhrig, 2008). Characteristics suggesting vulnerability (such as low income, being unemployed, having low levels of education, or being in poor health, elderly or divorced) decrease the likelihood of participation. Vulnerable groups may also be more prone to moving, and therefore making it difficult to locate and contact them, and survey questions related to their vulnerability (e.g., on poverty, divorce, health issues) may make them uncomfortable, so they choose not to respond (Gerry & Papadopoulos, 2015; Rothenbühler & Voorpostel, 2016; Uhrig, 2008). Sample members may have a combination of these characteristics which heighten the likelihood of nonresponse, especially if the survey questions asked are related (as mentioned previously). For example, it is known that women are more likely to respond than men, and this may be due to higher likelihood of them being at home caring for dependants (Watson & Wooden, 2009).

Much of the research into understanding the correlates of survey participation uses methods that rely on the first instance of nonresponse as indication of attrition. However, by doing this, it ignores those who do not respond at one wave but do not completely attrite from the sample. Some sample members respond at every wave, some respond for a number of waves and then drop out (monotone attrition) and some respond intermittently (non-monotone attrition). This makes it difficult to capture some of the mechanisms that may underlie sample members' decision to respond. Theoretically, there are four such mechanisms: survey commitment, habit, panel fatigue and shock (Lugtig, 2014). High commitment can lead to continued participation, whereas low commitment can lead to attrition, especially in the early waves of the survey as sample members do not feel obliged to participate (Laurie et al., 2004). As sample members continue to participate, a habit can be formed whereby the decision to participate becomes unconscious. If this habit is broken though, the likelihood of attrition is high. Sample members may also experience panel fatigue, whereby participating in the survey after a period of time becomes a burden (Laurie et al., 2004). In addition, they may experience a sudden shock that causes them to stop participating. A shock could be a change in their personal circumstance (such as change in employment, incapacitation, bereavement, change in residence) or a change in the survey experience (such as sensitive questionnaire topics, change in survey mode).

It can be difficult to obtain direct information for respondents and nonrespondents that relates to the aforementioned mechanisms. However, methods such as latent class analysis and sequence analysis can be used to measure these mechanisms indirectly by focusing on the process by which sample members respond. Latent class analysis is used in the research of this thesis. It involves estimating respondents' propensity to respond, ranging from 0 (will not respond) to 1 (will respond). Respondents are then categorised into groups based on the patterns of these response propensities (Gerry & Papadopoulos, 2015; Lugtig, 2014; Watson & Wooden, 2014). A response pattern with high response propensities across waves would be a sign of commitment and potentially a habit. A response pattern with declining response propensities could be a sign of panel fatigue and a sudden decline could be a sign of shock. While analysts may not be able to ascribe the exact mechanism to each individual, classifying them based on their response patterns can also inform the way in which bias prevention and adjustment strategies are applied (Lugtig, 2014).

Other methods used to study (differential) nonresponse enable inferences to be made about likely survey estimate nonresponse biases. Actual nonresponse biases often cannot be quantified because information about relevant population values is not available. One such method are representativeness indicators (Schouten et al., 2012; Schouten et al., 2009). These quantify variation in sample member response propensities estimated given a set of auxiliary covariates available for both respondents and non-respondents. One variant, the Coefficient of Variation of the response propensities, quantifies the maximal absolute standardised nonresponse bias of estimates from the respondent dataset. In addition, partial indicator decompositions are available that quantify propensity variation associated with auxiliary covariates and their categories. These respectively enable identification of covariates that should be included in models underlying post-data collection bias adjustments to improve dataset quality (see also previously), and subgroups that for similar reasons should be targeted by bias prevention techniques (see Little and Vartivarian (2005); Nagelkerke (1991); Särndal (2011); Wagner (2010) for similar alternative indicators).

As noted previously, patterns of participation can vary between surveys even in the same country. In addition, the survey landscape is everchanging, due to survey mode shifts, technological advances, and societal changes. Hence, while there is already a wealth of existing research about survey participation, this knowledge must always be revisited and improved upon. In terms of mode shifts, in recent years many surveys that were traditionally face-to-face (F2F) have adopted a mixed-mode design that includes other modes such as telephone and web. This enables a wider range of sample members to be reached and financial and time costs to be reduced. In particular, web interviews cost less and have faster turnaround times than F2F interviews (Baker et al., 2010; Couper et al., 2007; Lugtig et al., 2014; Schonlau & Couper, 2017; Schonlau et al., 2009). As a result, the role of web interviews in these mixed mode design has gradually increased over time (Bianchi et al., 2017; Burton & Jäckle, 2020; Cornesse & Bosnjak, 2018; Couper et al., 2007; Nicolaas et al., 2014). However, since the mode also tends to be associated with lower response rates and greater differential sub-group nonresponse, at least at this point, other interview modes are still also being utilised (Cornesse & Bosnjak, 2018; Daikeler et al., 2020; Nicolaas et al., 2014).

This thesis uses data from the UK as it is widely recognised for its strengths in longitudinal studies. This particularly true with regard to *Understanding Society*: the UK Household Longitudinal Study (UKHLS) (University of Essex & Institute for Social and Economic Research, 2022). This survey is the UK's only nationally representative household panel study, it began in 2009. 40,000 households were initially sampled, and this has increased over time, for example, by incorporating the sample of its predecessor survey, the British Household Panel Survey (BHPS), that started in 1991 and achieved 18 waves of data (Institute for Social and Economic Research, 2022; University of Essex & Institute for Social and Economic Research, 2022). In this thesis, three aspects of survey participation in the UKHLS are investigated: 1) the identification of loyal respondents, and correlates of monotone and nonmonotone response; 2) how the recent COVID-19 pandemic impacted on survey dataset quality, in terms of likely nonresponse biases, and whether patterns in pre-pandemic surveys were predictive of similar in pandemic era surveys; and 3) the recruitment and retention of youth respondents. Findings from this research will contribute to our knowledge of survey participation, both in the UKHLS survey and in surveys more generally. It will also inform the use of bias prevention and bias adjustment techniques to improve the quality of UKHLS and other survey datasets.

Specifically, Chapter 1 investigates the long-term response behaviour of UKHLS sample members. This chapter uses latent class analysis, which enables non-monotone patterns of response to be studied in addition to monotone patterns. Analyses focus on the BHPS sample of UKHLS, for which available data span a near thirty-year period. Given this time scale, measures to account for unknown eligibility are also incorporated in analyses. The research identifies loyal sample members who have responded to survey waves and characteristics and compares them to others in the panel. The implications of these findings on survey design are also discussed.

Chapter 2 considers the impact of the recent COVID-19 pandemic on survey dataset quality. Restrictions enforced in the pandemic led to the suspension of face-to-face interviewing, which tends to be the main mode in many large-scale panel surveys, and a shift to primarily web-based designs. Although similar mode shifts had been occurring pre-pandemic, it was at a slower pace and not to the same extent, so such design changes were implemented with limited knowledge on how they were likely to affect survey dataset quality and issues impacting on it. In light of this, this chapter investigates whether issues impacting on survey dataset quality, in terms of likely nonresponse biases, in the pre-pandemic mixed-mode UKHLS main survey predicted similar in the primarily web-based UKHLS COVID-19 Study. Representativeness indicators are used to quantify dataset quality in term of biases and issues impacting on it. Given the aforementioned pre-pandemic mode shifts, and a pattern of increasing use of web rather than F2F interviewing over time, the findings of this research have implications for survey design generally as well as for considerations of dataset quality in pandemic era surveys.

Chapter 3 investigates whether patterns of response among youths in the UKHLS main survey can predict their patterns of response in early adulthood. There is limited research on response patterns among children and youths, but generally younger sample members are more likely to attrite than their older counterparts. Hence, there is a need to understand recruitment and retention among younger respondents. In the UKHLS main survey, participants are invited to complete an adult (age 16+) or youth (age 10-15) questionnaire. This chapter uses latent class analysis to categorise the response patterns observed in UKHLS sample members' youth years and investigate whether they can predict early adulthood response. In addition, the role that parental response plays in the response patterns of young adults is quantified. The implications of these findings on survey design are also discussed.

This thesis concludes by summarising the findings of the research in the three chapters. Limitations are also discussed. Next, implications and contributions to literature are outlined and finally, recommendations for future research are considered.

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

Abstract

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:* The UK Household Longitudinal Study (UKHLS) is a household panel survey that began in 2009, following its predecessor, the British Household Panel Survey (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

1.1 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, 2009a). 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, 2013, 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 response (non-monotone attrition) 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 some attritors may instead have actually become ineligible for the survey.

1.1.1 Research Questions

This paper investigates sample members' patterns of response over survey waves in the British Household Panel Survey (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). Specifically, 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 (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 sub-groups that could benefit from targeted response inducement strategies that otherwise would not have been identified from focusing on monotone attrition (Lynn, 2013). This paper will first review the relevant literature in section 1.2. Then, outline the methods in section 1.3. It will then present the findings in section 1.4, where the key patterns of attrition are identified and the characteristics of those following these patterns are examined. Finally, the findings are summarised in section 1.5.

1.2 Literature Review

1.2.1 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 & Couper, 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 1.3.3).

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.

1.2.2 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 completely 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 to 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.

1.2.3 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 have investigated 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 political 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.

1.2.4 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, 2011b). 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 and Couper (2002)'s nonresponse framework, (Watson & 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 (Sadig, 2015; Watson, 2016). 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, 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. However, the differences were relatively small and mostly concerned those who were aged 60 and above in wave 1. This information was then used to create longitudinal nonresponse weights.

Similar to 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 investigate response patterns to learn more about attrition. While Lugtig (2014)'s 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 UKHLS, 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 (2014)'s 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.

1.3 Methods

1.3.1 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, the UKHLS 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; UKHLS, 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 UKHLS. This amounts to 26 waves because these individuals were not eligible to participate at wave 1 of UKHLS.

1.3.2 Repeated Measures Latent Class Analysis

Latent class analysis (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, 2010). 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, 2010). 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 Inc., 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. As such, 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 among 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 hence, has 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 & Willett, 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).

1.3.3 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 and as such reinforces why a combination of evaluation criteria is preferred to one single measure (Heron et al., 2015). 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 sex, 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, housing tenure, household size and number of reported moves. Moreover, there were covariates included related to political support and political interest (see Appendix A Table A1 for UKHLS specific variable names).

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 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 datasets (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; ONS, 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).

1.3.4 Unknown Eligibility

General population surveys aim to represent a study 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 study 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 Sadig (2014, 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 among 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 (ONS, 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).

$$\left(1 - q_{t,x}\right) \times \left(1 - q_{(t+1),(x+1)}\right) \times \ldots \times \left(1 - q_{26,(x+26-t)}\right)$$

where:

x is the age at last wave known to be alive.

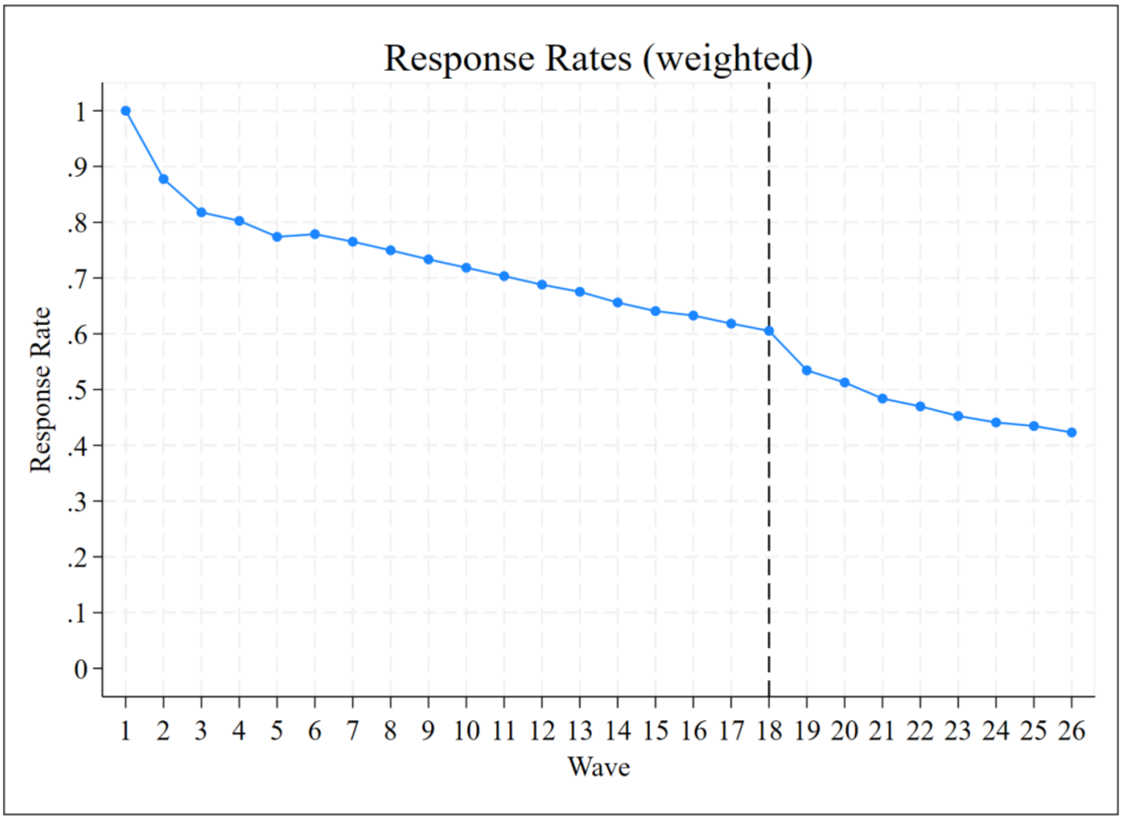
t is the last wave at which the individual was known to be eligible (alive).

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^{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 and standard errors adjust for the complex sample design using the primary sampling unit and strata.

1.4 Results

As noted in the Methods section 1.3.4, this section only contains the weighted analyses. These weighted analyses accounts for the estimated probability of the sample member being alive and as such, more accurately reflect the true population because the unweighted (see Appendix A) 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.

1.4.1 Patterns of Response



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.

Figure 1.1: Overall response rates (weighted)

Figure 1.1 depicts the overall weighted response rates, computed by the number of respondents who completed a full interview divided by the number of respondents estimated to be eligible to participate in the survey. Overall, the response rates show a declining pattern, decreasing to 0.42 in W26. Notably though, there are sharp decreases from W1 to W4 (0.80) and between W18 (0.61) and W19 (0.53). This reflects the aforementioned understanding that nonresponse is highest in the first few waves of the survey and a similar decline can be observed transitioning between BHPS and UKHLS. The unweighted response rates are very similar and are presented in Appendix A Figure A1.

In terms of patterns of response, a set of RMLCA nested models were estimated, where each model included an additional class when compared to the previous. Table 1.1 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 Appendix Table A2), the deviance and BIC statistics in Table 1.1 are generally lower. The entropy values are fairly similar in the unweighted and weighted models (ranging from 0.941-0.965), but generally, the unweighted models are slightly higher than in **Error! Reference source not found.**, 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.

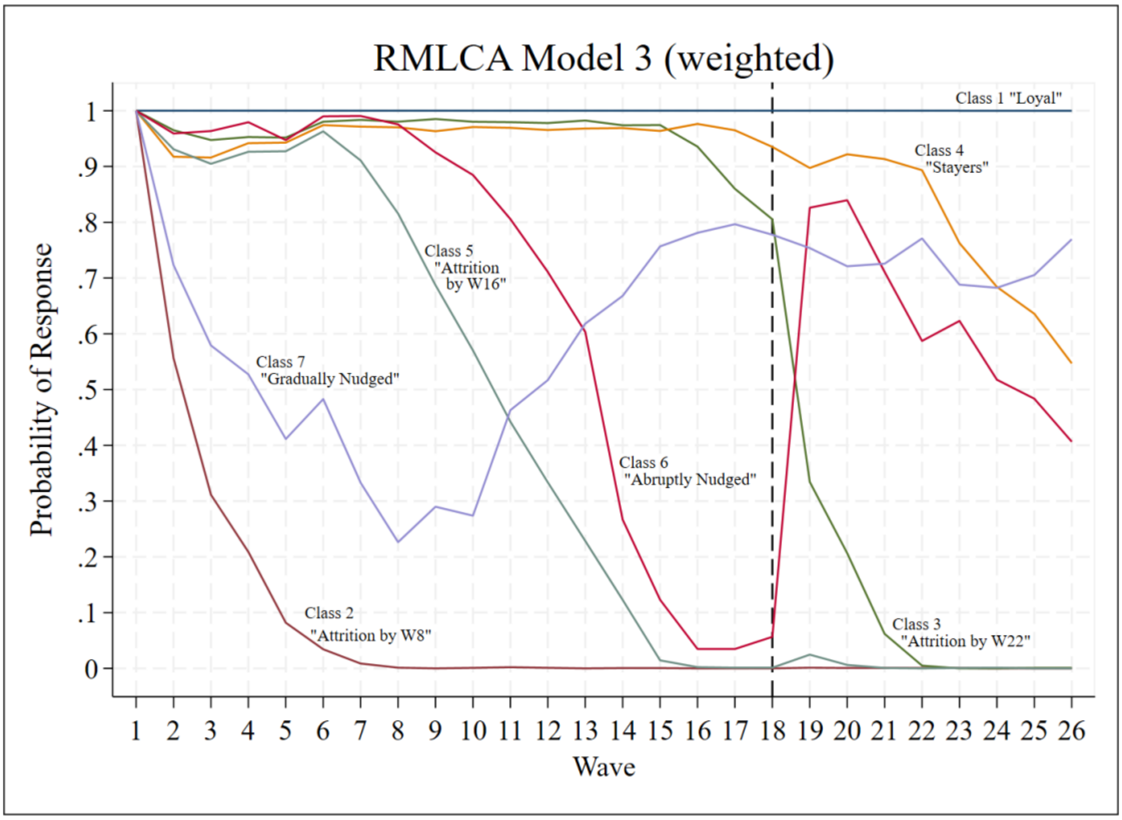
Table 1.1: Model fit information and statistics for the six best fitting models (weighted)

						Class Size (% of sample)		
Model	Number of Classes	Deviance	*df*	BIC (LL)	Entropy	Min.	Max.	BLRT
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	**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

Note: BIC = Bayesian Information Criterion; BLRT = Bootstrapped Likelihood Ratio Test.
N=9,912.
Deviance = –2 × Log Likelihood.
The lowest value of the BIC indicates a better fitting model (*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*). The model shown highlighted in bold typeface was selected as the final 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, which highlighted a noteworthy finding. As shown in Figure 1.2, 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 Appendix Figure A2). 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.



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.

Figure 1.2: Response probabilities for the weighted Model 3 (7 Classes)

Table 1.2: Summary statistics for the weighted Model 3

Class	Class Size	% of Sample	% of Female Respondents	Mean Age	% of Ethnic Minority Respondents
1	3,366.3	34	54	49	2
2	2,093.6	21	50	44	6
3	1,719.8	17	56	42	3
4	1,227.2	12	56	39	4
5	1,225.6	12	53	41	5
6	164.3	2	59	44	4
7	115.2	1	42	40	12
Total	9,912.0	100	54	44	4

Note: The class sizes are in decimals as the BCH method was adopted and adjustments to account for sample members with unknown eligibility were made.

The summary statistics for the weighted Model 3 are presented in Table 1.2 and the depiction of the classes and response patterns over the 26 waves are presented in Figure 1.2. 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 Appendix Table A3). 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 1.2, 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 response probabilities throughout BHPS but start 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.

1.4.2 Characteristics of Respondents

Table 1.3 and Table 1.4 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 1.3 depicts coefficients from Classes 2, 3 and 5, the classes that attrited at some point and Table 1.4 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 1.3 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 but slightly less likely than 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 1.4 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 (see Tables A3 and A4 in Appendix A). 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 A6 (see Appendix A) 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 55+) are more likely to be noncontacts than refusals, which suggests that younger respondents who refuse can be encouraged to participate again whereas for older respondents it is those who previously could not be contacted. The “gradually nudged” class is also more likely to have another reason for nonresponse besides noncontact and refusal (e.g., being ineligible).

Table 1.3: Multinomial regression coefficients of covariates on class membership (weighted)

	Attrition by W8 (Class 2)		Attrition by W22 (Class 3)		Attrition by W16 (Class 5)	
	Coef.	SE	Coef.	SE	Coef.	SE
Female	-0.16***	(0.05)	0.09*	(0.05)	0.01	(0.06)
Age (ref: 16-19)						
20-24	-0.17	(0.17)	-0.21	(0.17)	-0.37*	(0.19)
25-34	0.04	(0.15)	-0.02	(0.14)	-0.19	(0.16)
35-44	0.56***	(0.16)	0.15	(0.16)	0.25	(0.18)
45-54	1.65***	(0.20)	0.25	(0.17)	0.70***	(0.20)
55-64	2.44***	(0.24)	0.56***	(0.17)	0.94***	(0.24)
65+	2.84***	(0.22)	-0.08	(0.18)	1.05***	(0.24)
Ethnic Minority	0.63***	(0.21)	0.30	(0.20)	0.52**	(0.21)
Has Partner	-0.49***	(0.08)	0.14*	(0.09)	-0.07	(0.08)
Highest Qualification (ref: No qualification)						
Degree	-1.82***	(0.16)	-0.73***	(0.13)	-1.05***	(0.16)
Other higher degree	-0.95***	(0.15)	-0.36***	(0.13)	-0.79***	(0.17)
A-Level etc.	-0.83***	(0.12)	-0.13	(0.11)	-0.66***	(0.14)
GCSE etc.	-0.66***	(0.11)	-0.18*	(0.09)	-0.38***	(0.12)
Other qualification	-0.51***	(0.12)	0.04	(0.11)	-0.28**	(0.14)
Job (ref: Employed, in education or training)						
Unemployed	0.58***	(0.20)	-0.26	(0.23)	0.16	(0.21)
Retired	-2.63***	(0.15)	-0.60***	(0.12)	-1.42***	(0.14)
Other	-0.69***	(0.14)	-0.50***	(0.12)	-0.65***	(0.14)
Self-rated General Health (ref: Very poor)						
Excellent	2.28***	(0.19)	0.58***	(0.16)	1.04***	(0.18)
Good	1.62***	(0.18)	0.38***	(0.13)	0.58***	(0.16)
Fair	0.76***	(0.18)	0.04	(0.13)	0.21	(0.15)
Poor	0.31*	(0.18)	-0.01	(0.14)	0.07	(0.15)
Level of interest in politics (ref: Not at all int)						
Very interested	-0.08	(0.16)	-0.55***	(0.14)	-0.32*	(0.17)
Fairly int	-0.03	(0.11)	-0.35***	(0.09)	-0.25**	(0.10)
Not very int	-0.08	(0.10)	-0.32***	(0.09)	-0.19**	(0.10)
Supports a political party	-0.30***	(0.08)	-0.21***	(0.07)	-0.26***	(0.08)
Monthly Household Net Income (£000s)	-0.69***	(0.13)	-0.02	(0.05)	-0.12	(0.07)
No. of Own Children in the Household	-0.00	(0.08)	-0.11	(0.09)	0.04	(0.09)
No. of Pensioners in the Household	-0.43***	(0.09)	-0.02	(0.07)	-0.37***	(0.09)
Dwelling type (ref: Own entrance)						
Flats and other multi-storey units	0.50***	(0.11)	-0.13	(0.13)	0.33***	(0.12)
Bedsits/institutions/other structures	-0.16	(0.24)	-0.08	(0.18)	-0.02	(0.22)
Own Home	-0.21**	(0.09)	0.01	(0.09)	-0.09	(0.11)
Household Size	0.57***	(0.05)	0.39***	(0.05)	0.36***	(0.05)
No. of Reported Moves	1.03**	(0.46)	1.25***	(0.28)	2.07***	(0.31)
Constant	-1.38***	(0.29)	-1.11***	(0.22)	-1.02***	(0.28)

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 and 5. The coefficients are rounded to 2 decimal places. Standard errors in parentheses.
* $p < .05$. ** $p < .01$. *** $p < .001$. N = 348,133 (Weighted N = 9,912). Pseudo $R^2 = .11$

Table 1.4: Multinomial regression coefficients of covariates on class membership (weighted)

	Stayers (Class 4)		Abruptly Nudged (Class 6)		Gradually Nudged (Class 7)	
	Coef.	SE	Coef.	SE	Coef.	SE
Female	0.10	(0.07)	0.16	(0.14)	-0.57***	(0.16)
Age (ref: 16-19)						
20-24	-0.09	(0.18)	0.28	(0.44)	-0.58	(0.37)
25-34	-0.29*	(0.17)	0.36	(0.37)	-0.96***	(0.34)
35-44	-0.76***	(0.20)	0.28	(0.40)	-0.92**	(0.39)
45-54	-0.86***	(0.22)	0.04	(0.41)	-1.19***	(0.42)
55-64	-0.88***	(0.23)	-0.23	(0.49)	-0.92*	(0.51)
65+	-2.00***	(0.24)	-0.17	(0.46)	-1.60***	(0.47)
Ethnic Minority	0.32*	(0.19)	0.33	(0.47)	1.44***	(0.37)
Has Partner	-0.45***	(0.09)	-0.21	(0.18)	-0.13	(0.22)
Highest Qualification (ref: No qualification)						
Degree	0.03	(0.13)	-0.81***	(0.34)	-0.73*	(0.38)
Other higher degree	0.04	(0.13)	-0.35	(0.27)	-0.01	(0.38)
A-Level etc.	0.19	(0.12)	-0.23	(0.23)	-0.38	(0.29)
GCSE etc.	0.16	(0.10)	-0.38	(0.23)	0.24	(0.26)
Other qualification	0.00	(0.13)	0.03	(0.22)	0.25	(0.34)
Job (ref: Employed, in education or training)						
Unemployed	-0.39*	(0.23)	0.33	(0.49)	0.34	(0.43)
Retired	0.09	(0.15)	0.11	(0.28)	-0.52	(0.34)
Other	-0.52***	(0.16)	-0.31	(0.31)	0.40	(0.26)
Self-rated General Health (ref: Very poor)						
Excellent	-0.57***	(0.16)	-0.50	(0.33)	-0.25	(0.41)
Good	-0.71***	(0.14)	-0.19	(0.29)	-0.19	(0.26)
Fair	-0.40***	(0.11)	-0.32	(0.27)	-0.39	(0.27)
Poor	-0.20	(0.12)	-0.28	(0.30)	0.04	(0.30)
Level of interest in politics (ref: Not at all int)						
Very interested	-0.19	(0.14)	-0.09	(0.29)	0.12	(0.35)
Fairly int	-0.25**	(0.11)	-0.15	(0.22)	-0.25	(0.27)
Not very int	-0.15	(0.10)	-0.08	(0.21)	-0.04	(0.25)
Supports a political party	-0.01	(0.08)	-0.26*	(0.15)	-0.03	(0.20)
Monthly Household Net Income (£000s)	0.08	(0.05)	-0.04	(0.11)	-0.49*	(0.26)
No. of Own Children in the Household	-0.13	(0.09)	-0.20	(0.17)	0.03	(0.15)
No. of Pensioners in the Household	0.30***	(0.07)	0.04	(0.16)	0.27*	(0.16)
Dwelling type (ref: Own entrance)						
Flats and other multi-storey units	-0.20	(0.13)	-0.17	(0.26)	0.34	(0.27)
Bedsits/institutions/other structures	-0.03	(0.19)	0.52	(0.42)	0.20	(0.48)
Own Home	-0.03	(0.09)	0.40**	(0.20)	0.36	(0.24)
Household Size	0.29***	(0.06)	0.34***	(0.09)	0.19	(0.13)
No. of Reported Moves	1.12***	(0.27)	1.19***	(0.49)	1.00	(0.62)
Constant	-0.41	(0.25)	-3.43***	(0.50)	-2.23***	(0.60)

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, 6 and 7. The coefficients are rounded to 2 decimal places. Standard errors in parentheses.
* $p < .05$. ** $p < .01$. *** $p < .001$. N = 348,133 (Weighted N = 9,912)

1.5 Discussion

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 nonresponse. Therefore, another recommendation for future research is to separate response into contact and cooperation (Lepkowski & Couper, 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 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 not only be beneficial for further insight into panel attrition but also increasing participation in panel surveys.

2. Survey Mode Change by Necessity: Evaluating survey dataset quality during a global pandemic

Abstract

The COVID-19 pandemic significantly affected how surveys were administered. One change was suspending face-to-face (F2F) interviewing, the primary mode for many surveys, and shifting to primarily web-based designs. Another was more frequent data collection. Although the former mode shift had already been occurring in surveys pre-pandemic, albeit at a slower pace and not to the same extent, these design changes were made with limited information on their effect on dataset quality, in terms of likely nonresponse biases, and issues impacting on it. This paper investigates the extent to which information on such questions in pre-pandemic surveys was predictive of similar pandemic surveys in two surveys fielded by *Understanding Society*: the UK Household Longitudinal Study (UKHLS). The UKHLS main survey is an annual panel survey with a mixed mode (including F2F) design. In response to the pandemic, the UKHLS COVID-19 Study was fielded, in which main survey participants were invited to complete (mostly) bi-monthly web questionnaires. Representativeness indicators are used to quantify dataset quality in term of biases and issues impacting on it. Longitudinal datasets including respondents who have also responded in all prior waves are considered along with cross-sectional datasets. Findings suggest that information on (issues impacting on) dataset quality in main survey is of limited value for predicting similar in the COVID-19 Study. The implications of these findings, both for surveys during the pandemic and for surveys more generally, are then discussed.

Keywords: survey dataset quality; nonresponse bias; panel surveys; attrition; UK Household Longitudinal Study; representativeness indicators; mixed mode designs

2.1 Introduction

General population panel surveys aim to collect data from a sample that reflects a study population, typically a country, over time. However, a challenging issue observed over the last three decades is that fewer sample members are responding to surveys (de Leeuw & de Heer, 2002; Luiten et al., 2020). Nonresponse is important because it reduces survey dataset size, which can decrease the precision of survey estimates (Groves et al., 2009). In addition, survey dataset quality can also be affected if nonresponse occurs differentially for different subgroups of sample members (i.e., when nonresponse is non-random). This can cause survey estimates to deviate from the study population values (nonresponse biases), which can lead to invalid inferences. General population panel surveys follow participants over time, so a particular concern in this context is attrition, where a sample member drops out of the survey completely. A further complication in such surveys is the dynamic nature of the population, due to events such as births, deaths, and migration.

There are various ways survey designers or researchers can seek to maximise survey dataset quality in terms of minimising nonresponse biases. Bias prevention techniques, such as incentives offered to sample subgroups with otherwise lower response rates or refreshment samples, are implemented before or during the fieldwork period to increase the extent to which respondents reflect the eligible sample (Groves, 2006; Groves et al., 2009; Peytchev et al., 2010; Singer & Ye, 2013). In addition, bias adjustment techniques, such as supplying nonresponse weights (e.g., Bianchi and Biffignandi (2017); Lynn and Kaminska (2010); Valliant et al. (2018)); (see Carpenter and Kenward (2012); Kenward and Carpenter (2007); Little and Rubin (2020) for alternative methods), are implemented after the fieldwork period to reduce remaining biases. It should also be noted that an interaction exists between bias prevention and bias adjustment techniques; successful implementation of bias prevention techniques improves the effectiveness of bias adjustment techniques (Moore et al., forthcoming; Schouten et al., 2016).

2.1.1 Quantifying Survey Dataset Quality

When seeking to maximise survey dataset quality in terms of minimising survey estimate nonresponse biases, it is useful to be able to quantify biases. However, this is often impossible because nonrespondent information does not exist and population values are generally unknown (see Hand et al. (2018) for discussion). In early work, the survey response rate was often used as an indirect quality indicator, with higher rates presumed to indicate lower biases (Schouten et al., 2012; Schouten et al., 2011). However, subsequent empirical work has failed to demonstrate the expected correlation between response rates and biases (Groves, 2006; Groves & Peytcheva, 2008; Schouten et al., 2009), so methodologists have sought alternative indicators.

One set of indicators that have proven useful in this regard are representativeness indicators (Schouten et al., 2012; Schouten et al., 2009; Schouten et al., 2016). These evaluate how well respondents reflect the eligible sample by quantifying variation in sample member response propensities (their probabilities of responding to the survey estimated given auxiliary information available for both respondents and nonrespondents). Low levels of propensity variation suggest that respondents are a random subset of the sample with respect to auxiliary covariate values i.e., that they are representative of it (– also see section 2.2.2). This implies high survey dataset quality whether or not bias adjustment techniques are subsequently utilised since the effectiveness of such techniques increases with dataset representativeness (see section 2.1). In addition, partial indicators exist that decompose propensity variation into that associated with auxiliary covariates and their categories. These enable identification of covariates that should be included in models underlying bias adjustments to improve dataset quality in the former case, and of under-represented sample sub-groups that for similar purposes should be targeted by bias prevention techniques in the latter (for alternative indicators, see Little and Vartivarian (2005); Nagelkerke (1991); Särndal (2011); Wagner (2010)).

2.1.2 Survey Mode and Dataset Quality

Survey mode, the method by which sample members are interviewed, can play an important role in survey dataset quality. Interviews may be conducted face-to-face (F2F), by telephone, paper self-completion, and/or via the web. Often, surveys employ a combination of these methods i.e., are mixed mode. In the context of the nonresponse bias, mode can influence sample members' decisions to participate, and lead to differential subgroup nonresponse (Bianchi et al., 2017). F2F interviewing has traditionally been used as the mode of choice for general population surveys, especially in the UK. It is associated with higher response rates, but also has higher financial and time costs than other modes. More recently, web interviewing has become increasingly utilised due to lower financial costs, faster turnaround time and reaching a wider range of sample members (Baker et al., 2010; Couper et al., 2007; Lugtig et al., 2014; Schonlau & Couper, 2017; Schonlau et al., 2009). However, web response rates tend to be lower and differential subgroup nonresponse higher than with other modes (Cornesse & Bosnjak, 2018; Daikeler et al., 2020; Nicolaas et al., 2014). Hence, although the proportion of web interviews has tended to increase over time, many surveys currently employ a mixed mode design (Bianchi et al., 2017; Burton & Jäckle, 2020; Cornesse & Bosnjak, 2018; Couper et al., 2007; Nicolaas et al., 2014).

2.1.3 The COVID-19 Pandemic and Survey Dataset Quality

The influence of survey mode on survey dataset quality mentioned in the previous section became particularly important during the recent global COVID-19 pandemic. This was declared in March 2020 due to the rapid spread and impact of the SARS-CoV-2 virus. In most countries across the globe, preventative measures were implemented to stop the spread of the virus, including quarantining infected individuals and restricting human movement and social interactions (Onyeaka et al., 2021). Regarding the latter restrictions, in the UK the government announced a national lockdown, which involved staying at home and only leaving for essential purposes (including school closures and furloughing of non-essential jobs if remote working was not possible), and a social distancing policy (Prime Minister's Office, 2020).

These restrictions also had a significant impact on survey organisations. Regarding existing surveys, they generally meant that F2F interviewing could no longer be undertaken, and hence that alternative modes had to be utilised for data collection. In most cases, web interviewing, sometimes in combination with telephone interviewing, was instead used. As noted in section 2.1.2, similar changes in interview modes had been occurring pre-pandemic, but at a slower pace and not to the extent that was now necessary (Rathje & Glemser, 2021; Sastry et al., 2020; Voorpostel et al., 2021; Watson et al., 2021). Consequently, there was limited information on how they were likely to impact on the quality of survey datasets, in terms of likely nonresponse biases, or on quality issues in terms of response propensity variation associated with auxiliary covariates and their categories (the potential causes of biases) that may be addressed using bias prevention and/or bias adjustment techniques.

In addition, the pandemic generated a global need for information concerning its impacts and those of associated government policy responses. Given that there was also a requirement for such information to be made available in a timely manner, this need often could not be met by existing surveys, which tend to release datasets annually (Blom et al., 2020; Brown et al., 2021; Burton et al., 2020; Gummer et al., 2020). Hence, new surveys that collected information from participants more frequently were fielded (e.g., Blom et al. (2020); Brown et al. (2021); Burton et al. (2020); Gummer et al. (2020)). As well as the increase in the frequency of data collection, these new surveys were also subject to the aforementioned restrictions on interview mode. Hence, they were also implemented with limited information on how their designs were likely to impact on survey dataset quality and dataset quality issues.

An example of the above occurred with *Understanding Society*: the UK Household Longitudinal Study (UKHLS), an annual household panel survey (Institute for Social and Economic Research, 2022). When the survey began in 2009, interviews were entirely F2F. Subsequently, telephone and later web interviewing were introduced, so that it became mixed mode. When the national lockdown was declared, the UKHLS had to suspend face-to-face interviewing and conduct interviews only by web or telephone. The pandemic also led to a new, more frequent (monthly or bi-monthly for most of the pandemic), primarily web-based survey being fielded, the UKHLS COVID-19 Study. The COVID-19 Study eligible sample consisted of main survey participants, with the Study questionnaires focusing on the changes in their lives due to the pandemic (Burton et al. (2020); Institute for Social and Economic Research (2021b); see also section 2.2.1 for details of the two surveys). As with other surveys during this period, both of these surveys were undertaken with limited information on how their designs in terms of data collection frequency and interview modes were likely to the impact on survey dataset quality and dataset quality issues.

2.1.4 Research Questions

As noted in the previous section, during the COVID-19 pandemic, surveys were subject to changes in interview modes and interview frequencies that were implemented with limited information on how they would affect dataset quality in terms of likely nonresponse biases and issues impacting on it. Subsequently, little research has been published on how such changes did affect dataset quality, or on whether dataset quality and issues impacting on it and quality issues in terms of response propensity variation associated with auxiliary covariates and their categories (which potentially cause nonresponse biases and may be addressed using bias prevention and adjustment techniques) in pre-pandemic era surveys were similar to those in pandemic era surveys (i.e., whether knowledge of the former was useful in predicting the latter).

These questions are of broad relevance to survey designers beyond the COVID-19 pandemic. While the extent of the pandemic was unprecedented, at least in recent times, similar could happen again, with comparable impacts on survey interview modes and data collection frequencies. In addition, even without such events, web interviews may come to completely replace F2F interviews in survey designs due to their benefits (increased reach and reduced time and financial costs), so information on (issues impacting on) dataset quality in surveys in which the latter are not used at all is of value. This paper will address these knowledge gaps by evaluating and comparing the quality of the pre-pandemic UKHLS main survey datasets and the UKHLS COVID-19 Study datasets (University of Essex & Institute for

Social and Economic Research, 2021, 2022). Specifically, the research questions investigated are:

1. How does the quality in terms of likely nonresponse biases of the pre-pandemic UKHLS main survey datasets, in which F2F interviewing was utilised, compare to that of the primarily web-based and more frequently collected UKHLS COVID-19 Study datasets?

2. How do dataset quality issues (in terms of response propensity variation associated with auxiliary covariates and their categories that may cause nonresponse biases) compare in the two surveys?

To evaluate dataset quality in terms of likely nonresponse biases and to identify potential quality issues, representativeness indicators are used. The paper proceeds as follows. First, in section 2.2, the considered surveys are described, representativeness indicators are detailed, and the evaluation methods used in the research are outlined. Second, in section 2.3, the results of the analyses are reported. Third, in section 2.4, the implications of these results for survey design are discussed.

2.2 Methods

2.2.1 Data

Understanding Society: The UK Household Longitudinal Study (UKHLS) is an annual household panel survey that began in 2009. It was developed as a successor of and includes sample members from the British Household Panel Survey (BHPS), which began in 1991 and continued for 18 waves until 2008. The UKHLS sample is built from probability samples.

The wave 1 sample consisted of the General Population Sample (GPS) and Ethnic Minority Boost Sample (EMBS), which were respectively representative of the UK population and the ethnic minority population at the time (Lynn, 2009b; Lynn & Kaminska, 2010). 52,941 GPS and EMBS households (HHs) were sampled in Wave 1. Of these, 30,032 HHs had at least one member provide an interview and 47,732 respondents completed full interviews (Lynn & Knies, 2016). The survey is ongoing and by the end of 2022, 12 waves of data had been released (Institute for Social and Economic Research, 2022). The survey was predominantly face-to-face until Wave 3, when a small number of telephone interviews were introduced. Then in Wave 7, web interviews were introduced, and in each wave since, the proportion of the sample invited to complete a web interview has increased (to a maximum of 70%) (Institute for Social and Economic Research, 2022). The interview consists of an enumeration grid that identifies and collects basic information about HH members, a HH interview and individual interviews. In total, it should take approximately an hour to complete.

In response to the pandemic, the UKHLS team fielded the *Understanding Society* COVID-19 Study, a primarily web-based survey that asked participants about the impact of the pandemic and associated government policy responses (Burton et al., 2020). The first wave of the Study was fielded in April 2020, with further monthly surveys until July 2020, then bimonthly surveys from September 2020 to March 2021, and then a final survey in September 2021 (Institute for Social and Economic Research, 2021b). Individuals living in HHs that had participated in one of the two latest main survey waves at the time (waves 8 and 9) were eligible to participate (excluding those who had died, moved abroad or adamantly refused to take part). Sample members received a pre-notification letter by post in April 2020 informing them about the survey (see Figure B1 in Appendix B for pre-notification letter and Institute for Social and Economic Research (2021a) for further participant communication materials).

A small financial incentive was offered for each survey completed, which could be exchanged for a range of gift-cards and electronic vouchers. From wave 2, rewards could be transferred into a charitable donation. Respondents were then invited to participate in each wave by email and/or text message (depending on the contact information held) (Institute for Social and Economic Research, 2021b). Wave 8 of the Study included additions such as COVID-19 serology (antibody) testing and a respondent incentive experiment, for which respondents were informed by post if there was no record of a valid email address. Those that participated in the serology testing received their results informing them of whether blood antibodies were clearly detectable or not (Institute for Social and Economic Research, 2021b). A total of 42,330 sample members were eligible to participate in Wave 1. In addition to the web interviews, the Study sought interviews from some web nonrespondents by telephone (Institute for Social and Economic Research, 2021b). However, as this only occurred twice (in May and November 2020), these telephone interviews are not considered in this paper. The survey consisted only of an individual interview, with a duration of approximately 20 minutes.

2.2.2 Representativeness Indicators

As noted in the Introduction, representativeness indicators provide a measure of survey dataset quality in terms of likely nonresponse biases. They evaluate how well respondents reflect the eligible sample by quantifying variation in sample member estimated response propensities. Response propensities are estimated with logistic regression modelling using auxiliary information (covariates) available for both respondents and nonrespondents. These covariates should correlate with the probability of response and the survey variables of interest (Roberts et al., 2020). The R-indicator is the most well-known form of a representativeness indicator (Schouten et al., 2012; Schouten et al., 2009). The overall R-indicator, which quantifies overall dataset quality, is the standard deviation of the survey sample member response propensities $S(\rho_X)$ transformed to the 0-1 scale:

$$R(\rho_X) = 1 - 2S(\rho_X) \tag{1}$$

where the ρ_X denotes the response propensities of sample members given the auxiliary covariates, X (Schouten et al., 2012). An indicator of 1 indicates no response propensity variation (i.e., that the respondents are a random subset of the eligible sample with respect to auxiliary covariate values) and high dataset representativeness (Schouten et al., 2009; Schouten et al., 2016).

However, when comparing datasets with different response rates, as is undertaken in this paper, a representativeness indicator with better properties is the Coefficient of Variation of response propensities (CV). R-indicator accuracy is dependent on the response rate (Schouten et al., 2009), which is not an issue with the CV because it standardises the response propensity standard deviation $S(\rho_X)$ by the mean response propensity $\bar{\rho}$. The overall CV is

$$CV(\rho_X) = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\bar{p}_i - \bar{p})^2}}{\bar{\rho}} \tag{2}$$

where $\bar{p}_i$ is the estimated response propensity for subject i, and equation numerator equals $S(\rho_X)$. With this indicator, a value of 0 indicates no response propensity variation and high representativeness (de Heij et al., 2015; Moore et al., 2018; Nishimura et al., 2016; Schouten et al., 2016). A further advantage of the overall CV is that it predicts the maximal standardised nonresponse bias of survey variable means (Schouten et al., 2016; Schouten et al., 2011) i.e., it measures dataset quality on a scale interpretable by survey designers.

While the magnitude of the overall CV provides information about the extent of maximal absolute bias, it cannot identify the specific survey variables that are affected, nor can it be used to identify bias causation. i.e., the correlates of response propensity variation. For the latter, partial CV decompositions are a useful tool. These quantify response propensity variation associated with auxiliary covariates and covariate categories. There are two types of partial indicators, unconditional (CV_us) and conditional (CV_cs), with both types available at both the covariate and covariate category levels. Covariate CV_us are derived from the between variation decomposition components and measure univariate associations between auxiliary covariates and response propensity variation. That is, they measure the contribution of response propensity variation associated with the covariate, Z, to dataset non-representativeness (Schouten et al., 2011). This is useful for identifying covariates that should be included in models underlying bias adjustments to improve dataset quality (see Moore et al. (2021)). The covariate CV_u is

$$CV_u(Z, \rho_X) = \frac{\sqrt{\frac{1}{n}\sum_{k=1}^{K} n_k(\bar{p}_k - \bar{p})^2}}{\bar{\rho}} \tag{3}$$

where K is the number of categories in covariate Z, n_k is the number observations in category, k and $\bar{p}_k$ is the mean response propensity in category k. A CV_u of 0 implies no non-representativeness associated with the covariate i.e., that respondents are a random subset of the eligible sample with respect to values of the considered covariate. Covariate CV_cs are derived from the within variation decomposition components and measure multivariate associations between response propensity variation and auxiliary covariates. That is, they measure the contribution of response propensity variation to dataset non-representativeness associated with a covariate, Z, contributes after taking into account the impact of other auxiliary covariates, i.e., they measure the contribution that is solely associated with the covariate (Schouten et al., 2011). This is useful for ensuring that covariates identified as being associated with response propensity variation do not exhibit such a relationship because they are correlated with other covariates (overfitting of covariates in models underlying bias adjustments can lead to over-inflated survey estimate variances – see Little and Vartivarian (2005)). The covariate level CV_c is

$$CV_c(Z,\rho_X) = \frac{\sqrt{\frac{1}{n}\sum_{l=1}^{L}\sum_{i\in l}(p_i - \bar{p}_l)^2}}{\bar{\rho}} \tag{4}$$

where $\bar{p}_l$ is the mean response propensity of the lth of L cells in a cross-classification of X excluding Z, and X is the covariate subset for the propensity modelling. A CV_c of 0 indicates no non-representativeness solely associated with the covariate i.e., that respondents are a random subset of the eligible sample with respect to the covariate when the impacts of the other covariates are accounted for. Both CV_us and CV_cs are bounded by the overall CV. Category level CVs are similarly derived and share similar interpretations to the covariate level counterparts (Schouten et al., 2011). They are useful for identifying under-represented sample sub-groups that should be targeted by bias prevention techniques to improve dataset quality. The CV_u for the category, k, of covariate, Z, is

$$CV_u(Z_k, \rho_X) = \frac{\sqrt{\frac{n_k}{n}}(\bar{\rho}_k - \bar{\rho})}{\bar{\rho}} \tag{4}$$

where n_k is the size of the covariate category, k, and $\bar{\rho}_k$ is the mean response propensity in category, k. With this indicator, negative values indicate that the category in question is under-represented in the respondent dataset, positive values that it is over-represented, and a zero value that it does not contribute to the non-representativeness i.e., that respondents are a random subset of the eligible sample with respect to the considered category. The category CV_c is

$$CV_c(Z_k, \rho_X) = \frac{\sqrt{\frac{1}{n-1}\sum_{l=1}^{L}\sum_{i \in l} h_i(p_i - \bar{p}_l)^2}}{\bar{\rho}} \tag{5}$$

where h_i indicates whether subject, i, is in category, k. With this indicator, larger positive values indicate higher solely associated contributions to non-representativeness and zero values no solely associated contribution i.e., that respondents are a random subset of the eligible sample with respect to the category when the impacts of the other covariates are accounted for. It is useful for identifying correlations between categories, and so preventing unnecessary applications of bias prevention techniques. In addition to the indicators themselves, approximate indicator standard errors (SE) are available that can be converted into 95% confidence intervals (CIs) (i.e., $95\%\ CI = indicator \pm (1.96 \times standard\ error)$). These can be used to evaluate indicator statistical significance (de Heij et al., 2015; Moore et al., 2021; Shlomo & Schouten, 2013; Shlomo et al., 2012). With (overall and partial) CVs, a value not significantly different from 0 indicates no associated non-representativeness.

2.2.3 Evaluation Methods

CVs are used to evaluate the quality, in terms of likely nonresponse biases, of the pre-pandemic UKHLS main survey and UKHLS COVID-19 Study datasets (University of Essex & Institute for Social and Economic Research, 2021, 2022). Both longitudinal (including respondents to the wave in question and all previous waves) and cross-sectional datasets are considered as both are of interest to analysts for different estimation purposes. Since indicators are dependent on the auxiliary covariates used in their computation, a difficulty when using them to compare surveys is that the same covariates are not available (Schouten et al., 2009). This is not an issue in the comparisons in this paper, because the same UKHLS main survey covariates from different survey waves are used.

That said, such auxiliary covariates are not available for the main survey wave 1 nonrespondents. Hence, for the evaluations of the main survey datasets, the analysis sample is defined as all wave 1 respondents (=46,885 individuals). The first wave of respondents evaluated is wave 2, then each wave after up to and including wave 9, the last wave completed pre-pandemic. In contrast, as eligible sample members were drawn from the main survey and the majority possessed main wave 9 information (some did not because they did not respond to the wave), evaluations of the COVID-19 Study datasets could begin with wave 1 respondents. However, for comparability with evaluations of the main survey datasets, the wave 1 respondent (with main survey wave 9 information) dataset (=14,777 individuals) was used as the analysis sample in the COVID-19 Study evaluations, with again the first wave of respondents evaluated from wave 2, then each wave up to and including wave 9 (the final Study wave). It should be noted with both surveys beginning evaluations with the wave 2 respondent dataset only applies to the cross-sectional respondent datasets. Evaluations of the longitudinal datasets, begin with the wave 3 respondents (having also responded to wave 2) datasets. Eight auxiliary covariates were included in the response propensity models and had their impacts on dataset representativeness quantified (see Table 2.1 for details). All of these had previously been shown to have impacts on UKHLS main survey sample member response propensities or the response propensities of sample members in other panel surveys (see, for example, Lugtig et al. (2014); Lynn and Borkowska (2018); Uhrig (2008)). Sample members with missing values for any of the covariates were removed from the analysis datasets.

In the evaluations, wave 1 nonresponse weights supplied with the two surveys, are also applied to their respective analysis samples. In the case of the UKHLS main survey, this weight is 'a_indinus_xw', which is the survey selection weight adjusted for wave 1 nonresponse. In the COVID-19 Study, it is 'ca_betaindin_xw', which is the main survey wave 9 cross-sectional weight (which are the survey selection weight adjusted for waves 1-9 nonresponse then post-calibrated to 2019 UK estimated population totals) adjusted for COVID-19 Study nonresponse (see Institute for Social and Economic Research (2021b, 2022) for more details of these weights).

These weights are primarily applied to map the analysis samples (which, as mentioned, consist of wave 1 respondents only) to the respective survey eligible samples, so that likely nonresponse biases measured are in comparison to these samples. However, given their purpose outside of this study, they also map the two analysis samples (and quantify likely nonresponse biases in comparison) to the UK population at different time points: March 2009-January 2011 in the case of the main survey analysis sample, and June 2019 in the case of the COVID-19 Study eligible sample. It should be noted that this latter mapping is in theory: weights are imperfect. However, that said, empirical work has shown that the main survey weighted survey estimates perform well in approximating relevant population benchmark estimates (Benzeval et al., 2020; Borkowska, 2019). Moreover, when the COVID-19 Study wave 1 weights are used to weight respondent main survey wave 9 responses, summary estimates closely approximate similar main survey wave 9 weighted estimates (Moore et al., forthcoming). It should be noted that there was no alternative to using weights that (putatively) mapped analysis samples to the UK population at different time given the disparity in time periods covered by the data analysed from the two surveys. It should also be noted that the evaluations reflect the extent to which each survey sample adds additional nonresponse bias marginal to that already present in the baseline sample, rather than comparing how well each reflects the survey population as the baseline samples cannot be compared due to the COVID-19 Study eligible sample consisting of long-term main survey respondents who are likely positively disposed towards participation. Therefore, the evaluations do still address the study research questions of how well the (later) respondent datasets reflect their respective eligible samples/study populations, and whether there are commonalities in terms of correlates of variation in (weighted) analysis sample member response propensities.

To evaluate overall dataset quality, overall CVs and their 95% CIs are computed for each longitudinal and cross-sectional respondent dataset. In addition, to identify quality issues in terms of covariates and covariate categories associated with response propensity variation, auxiliary covariate, and covariate category partial CV_us and CV_cs and their 95% CIs are computed. To compute the indicators, the R syntax developed by The Representativity Indicators for Survey Quality (RISQ) project was used (de Heij et al., 2015; RStudio Team, 2021). Stata 16.1 was also used for data management and to produce graphs (StataCorp, 2019).

Table 2.1: Auxiliary covariates used in analyses

Auxiliary Covariate	No. of Categories	Categories
Sex (sex_dv)	2	Male; Female
Ethnicity (ethn_dv)	2	Not an ethnic minority; Ethnic minority
Age (age_dv)	7	16-19; 20-24; 25-34; 35-44; 45-54; 55-64; 65+
Employment Status (jbstat)	4	Employed, in education or training; Unemployed; Retired; Other
Household Composition (hhtype_dv)	6	1 adult, no children; 1 adult, children; Couple, no children; Couple, children; 2+ adults, no children; 2+ adults, children
Marital Status (marstat)	4	Single; Married; Separated/divorced; Widowed
Highest Qualification (hiqual_dv)	5	No qualifications; Degree or equiv.; A-Level or equiv.; GCSE or equiv.; Other
Housing Tenure (tenure_dv)	3	Owned; Rented; Other

Note: UKHLS specific variable names in parentheses.

2.3 Results

This section presents the results of the evaluations of UKHLS main survey and COVID-19 Study dataset quality. Graphs reporting response rates and Coefficients of Variation of response propensities (CVs) for the longitudinal datasets are presented in this section, and their cross-sectional dataset counterparts are presented in Appendix B. Tables that report exact CV values and CV 95% CIs are also presented in Appendix B.

2.3.1 Response Rates

Response rates for the longitudinal (responding to the mentioned wave and all waves prior) waves 3-9 UKHLS main survey and COVID-19 Study datasets are presented in Figure 2.1. These are computed as the number of respondents meeting the mentioned criteria divided by the number of analysis sample members (the number of wave 1 respondents: see section 2.2.3 for explanation and Appendix B Table B7 for tabulated rates). In the main survey, the rate at wave 3 is 0.61, then it decreases at a decreasing rate over waves to 0.30 at wave 9. In the COVID-19 Study, rates are higher, beginning at 0.71 at wave 3 and then decreasing over waves to 0.44 at wave 9. The rate of decrease is fairly constant until wave 6, then slows slightly to wave 7, slows even more to wave 8, before increasing again (though less than previously) to wave 9. It is likely that the changes from waves 7 to 9 are related to the serology testing for COVID-19 antibodies offered at wave 8 and the greater financial incentives offered at wave 8 and 9 (see section 2.2.1). These are likely to have slowed the drop-out by sample members who had responded to all previous waves. Why the rate of decrease reduced from waves 6 to 7 is unclear.

Response rates for the UKHLS main survey and COVID-19 Study cross-sectional datasets are presented in the Appendix Figure B2 (see Appendix Table B1 for tabulated rates). These are calculated as the number of respondents to the wave divided by the number of analysis sample members (i.e., wave 1 respondents). As would be expected given the less restrictive inclusion criteria, rates are higher than for the longitudinal datasets. In the main survey, the rate at wave 2 is 0.75, then it decreases at an uneven but slightly decreasing rate to 0.40 at wave 9. In the COVID-19 Study, a different pattern is observed. Rates are again higher than in the main survey. At wave 2, the rate is 0.79. It decreases at an increasing rate to 0.64 until wave 6, then increases to 0.69 by wave 8, then decreases again to 0.66 at wave 9. Similar to with the longitudinal response rates, post wave 7 it is likely that this latter pattern is related to the serology testing and greater financial incentives offered at waves 8 and 9. The increase in response rates implies that not only did these slow drop-out rates among those who had responded to all previous waves, they also led previous non-respondents to re-engage with the survey. Why response rates also increased from wave 6 to 7 is unclear.

2.3.2 Overall Coefficients of Variation of Response Propensities (CVs)

Table 2.2: Overall Coefficients of Variation (CV) for the UKHLS main and COVID-19 datasets, longitudinal

	Longitudinal CVs	
Wave	MAIN	COVID
3	**0.19 (0.18 - 0.19)**	**0.16 (0.15 - 0.17)**
4	**0.23 (0.22 - 0.24)**	**0.19 (0.18 - 0.21)**
5	**0.27 (0.26 - 0.28)**	**0.23 (0.22 - 0.24)**
6	**0.31 (0.30 - 0.32)**	**0.27 (0.25 - 0.28)**
7	**0.34 (0.33 - 0.35)**	**0.30 (0.28 - 0.31)**
8	**0.37 (0.36 - 0.38)**	**0.30 (0.29 - 0.32)**
9	**0.41 (0.39 - 0.42)**	**0.31 (0.30 - 0.33)**

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Overall CVs quantifying overall dataset quality for the UKHLS main survey and COVID-19 Study waves 3-9 longitudinal datasets are presented in Figure 2.1 (tabulated values and indicator 95% CIs are presented in Table 2.2). With overall CVs, lower values indicate higher representativeness. For both surveys, all are significantly different from 0, implying that overall dataset non-representativeness is non-trivial i.e., that respondents are a non-random subset of the (in this case weighted to map to the survey eligible sample, and putatively the UK population: see section 2.2.3) analysis sample with respect to auxiliary covariate values. They also increase, implying reduced representativeness, across survey waves. In the main survey, they increase at a relatively constant rate from 0.19 at wave 3 to 0.41 at wave 9. In the COVID-19 Study, they are slightly smaller, implying higher representativeness, and increase at a constant rate from 0.16 at wave 3 to 0.30 at wave 7, then increase at a lower rate to 0.31 by wave 9. This change in the rate of increase at waves 8 and 9 is likely to be related to the reduced drop-out rates of those who had responded to all previous waves that occurred at these waves due to serology testing and increased financial incentives being offered (see also section 2.3.1).

Overall CVs for the UKHLS main survey and COVID-19 Study cross-sectional datasets are presented in Appendix B Figure B2 (see Appendix B Table B2 for tabulated values and indicator 95% CIs). For both surveys, all are significantly different from 0, implying that overall dataset non-representativeness is non-trivial. They also mostly increase, implying reduced representativeness, across survey waves. In the main survey, they increase at a relatively constant rate from 0.12 at wave 2 to 0.32 at wave 9. In the COVID-19 Study they are slightly smaller and increase from 0.12 at wave 2 to 0.21 in wave 7, then decrease, implying increased representativeness, to 0.16 in wave 8 and 0.14 in wave 9. This increase at waves 8 and 9 is likely to be related to the reduced respondent drop out and sample member re-engagement with the Study that occurred at these waves due to serology testing and increased financial incentives being offered (see also section 2.3.1).

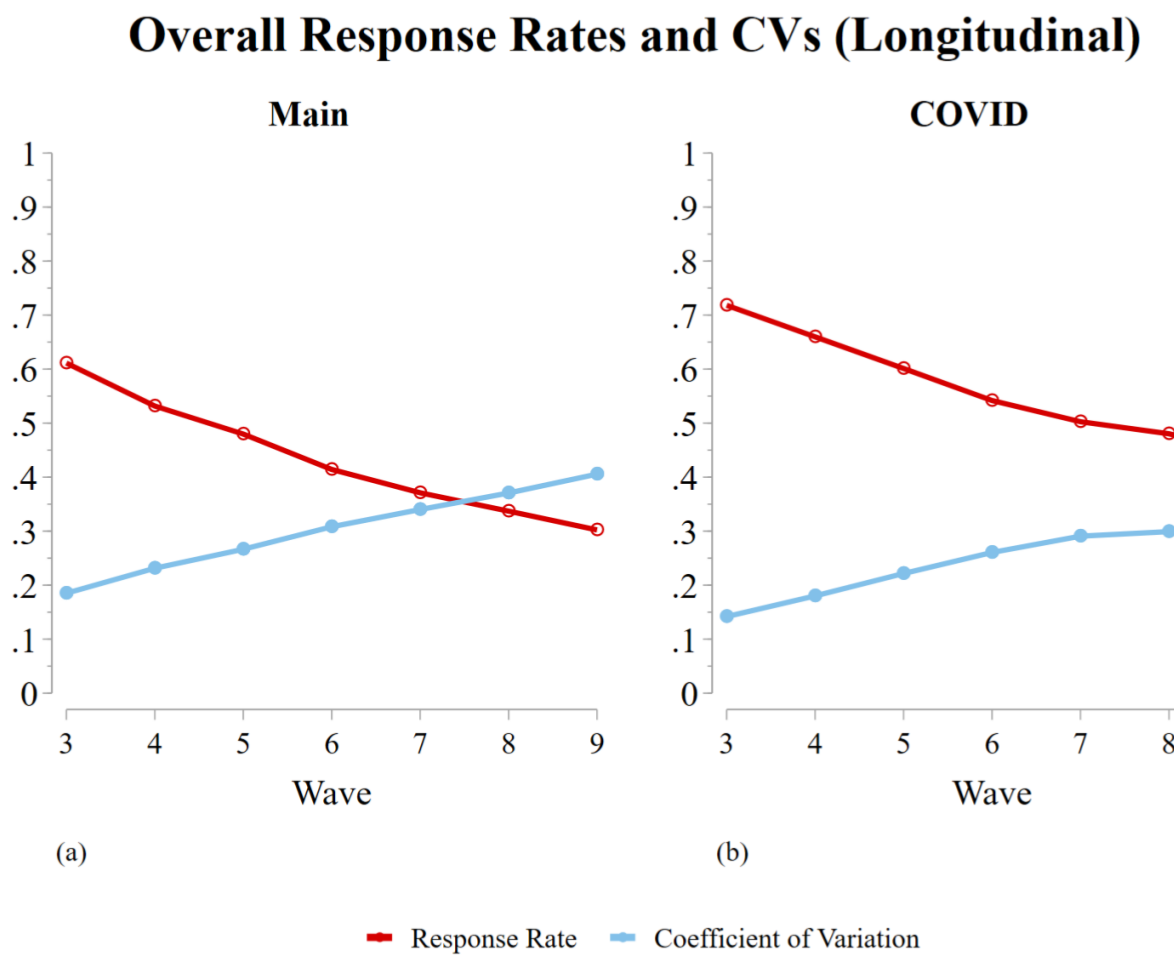


Figure 2.1: Response Rates and Overall Coefficients of Variation for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

2.3.3 Partial Covariate CVs

Partial unconditional covariate CVs (CV_us) for the UKHLS main survey and COVID-19 Study longitudinal datasets are presented in Figure 2.2 (tabulated values and indicator 95% CIs are presented in Appendix B Table B8). These quantify univariate associations between response propensity variation and auxiliary covariates, with zero values indicating no association i.e., that respondents are a random subset of the (in this case weighted) analysis sample with respect to the considered covariate. In the main survey, all covariate CV_us are statistically significantly different from 0, implying non-trivial associations with response propensity variation. Generally, but not always, CV_us for given covariates increase, implying increased associated non-representativeness, across waves. Of the covariates, Age has the highest CV_us, which increase from 0.14 at wave 3 to 0.29 at wave 9. Housing Tenure and Marital Status CV_us are similar but slightly smaller, increasing from 0.10 and 0.11 respectively at wave 3 to 0.21 at wave 9. Highest Qualification CV_us increase at a higher rate across waves than those for other covariates, from 0.05 at wave 3 to 0.18 at wave 9. Ethnicity and Household Composition CV_us also increase comparatively rapidly, from 0.08 at wave 3 to 0.13 and 0.15 respectively at wave 9. Employment Status CV_us are small, increasing from 0.06 at wave 3 to 0.08 at wave 9. Sex has the smallest CV_us of all, which increase very slightly from 0.03 at wave 3 to 0.04 at wave 4, then remain stable.

In the COVID-19 Study, longitudinal dataset CV_us are generally slightly smaller than in the main survey, implying less non-representativeness associated with covariates. Again, all are statistically significantly different from 0, implying non-trivial univariate associations with response propensity variation, and in many cases for a given covariate increase across waves. However, CV_us often stabilise at waves 8 and 9, likely due to the reduced drop-out rates among those who had responded to all previous waves that occurred at these waves in response to serology testing and increased financial incentives being offered (see also section 2.3.1). As with the main survey, Age has the largest CV_us, which increase from 0.11 to 0.24 at wave 7, then stabilise at waves 8 and 9. Beyond that, the ranking of covariates in terms of impact mostly differs from that in the main survey datasets. Household Composition has the second largest CV_us, which increase from 0.10 at wave 3 to 0.21 at wave 7, before also stabilising at waves 8 and 9. Next is Employment Status , with CV_us that increase from 0.08 at wave 3 to 0.16 at wave 7 then stabilise, then Marital Status, with CV_us that increase from 0.07 at wave 3 to 0.13 at wave 7, stabilise at wave 8, and then increase very slightly to 0.14 at wave 9. After this is Housing Tenure, with CV_us that increase from 0.05 at wave 3 to 0.14 at wave 9, then Ethnicity, with CV_us that increase from 0.05 at wave 3 to 0.10 at wave 9. The two smallest sets of CV_us are for Highest Qualification, for which an increase from 0.04 at wave 3 to 0.08 at wave 9 is observed, and Sex, for whom they increase slightly from 0.03 at wave 3 to 0.04 at wave 9.

CV_us for the UKHLS main survey and COVID-19 Study cross-sectional datasets are presented in Appendix B Figure B3 (tabulated values and indicator 95% CIs are presented in Appendix B Table B3). The indicators are a similar size to those for the longitudinal datasets. For the main survey, CV_us for all covariates are statistically significantly different from 0, and often, but not always, increase across waves. The ranking of covariates in terms of impact is comparable to that in the main survey longitudinal datasets. Age has the largest CV_us, which increase from 0.09 at wave 2 to 0.22 at wave 9. The next largest are for Housing Tenure, with an increase from 0.06 at wave 2 to 0.18 at wave 9 observed, Marital Status, with an increase from 0.07 at wave 2 to 0.15 at wave 9 observed, and Highest Qualification, whose CV_us (similar to in the longitudinal datasets) increase at a faster rate than for other covariates, from 0.02 at wave 2 to 0.17 at wave 9. Following this are Employment Status, whose CV_us remain between 0.04 and 0.05 until wave 6, then increase to 0.10 by wave 9, and Household Composition and Ethnicity, whose CV_us both increase from 0.05 at wave 2 to 0.09 at wave 9. CV_us for Sex are the smallest and increase only slightly from 0.02 at wave 2 to 0.03 at wave 9.

The COVID-19 Study cross-sectional dataset CV_us tend to be slightly smaller than main survey equivalents but are almost always statistically significantly different from 0 (the exception being the wave 4 Sex indicator). Again, in many cases for a given covariate they increase across waves. However, CV_us often also stabilise or decrease at waves 8 and 9, probably due to reduced respondent drop out and previous non-respondents re-engaging with the Study in response to serology testing and increased financial incentives being offered (see also section 2.3.1). The ranking of covariates in terms of impact is comparable to that in the COVID-19 Study longitudinal datasets, but mostly differs that in the main survey datasets. Age has the largest CV_us, which increase from 0.08 at wave 2 to 0.17 at wave 7, then decrease to 0.10 by wave 9. The next largest are those for Household Composition, which increase from 0.06 at wave 2 to 0.13 at wave 7, then decrease to 0.07 by wave 9, then those for Employment Status, which increase from 0.04 at wave 2 to 0.11 at wave 7, then decrease 0.05 by wave 9, and Marital Status, which increase from 0.06 at wave 2 to 0.10 at wave 7, then decrease to 0.08 by wave 9. Following this are the CV_us for Housing Tenure, which increase from 0.04 at wave 2 to 0.08 at wave 7, then decrease to 0.06 by wave 9, and the CV_us for Highest Qualification, which increase and decrease across waves, starting at 0.04 in wave 2 ending at the same value at wave 9, with CV_us at their lowest at wave 4 (0.02) and their highest in wave 6 (0.05). Then are the CV_us for Ethnicity, which increase from 0.04 at wave 2 to 0.06 at wave 7, then decrease to 0.03 by wave 9. Sex CV_us are the smallest of all and begin at 0.02 at wave 2 before increasing and decreasing across waves to end at 0.04 at wave 9.

Partial conditional covariate CVs (CV_cs) for the UKHLS main survey and COVID-19 Study longitudinal datasets are presented in Figure 2.3 (tabulated values and indicator 95% CIs are presented in Appendix B Table B9). CV_cs consider multivariate associations between auxiliary covariates and response propensity variation, and quantify the non-representativeness solely associated with the covariate. Zero values indicate no non-representativeness i.e., that respondents are a random subset of the (in this case weighted) eligible sample with respect to the covariate when the effects of the other covariates are accounted for. Main survey CV_cs are all smaller than their CV_u analogues, suggesting correlations between covariate impacts, but are also almost always statistically significantly different from 0 (the exceptions are several Employment Status CV_cs), implying non-trivial solely attributable non-representativeness. In addition, for a given covariate they often increase across waves, suggesting that such non-representativeness increases. The ranking of covariates in terms of impact is comparable to that with CV_us. Age CV_cs are largest and increase from 0.07 at wave 3 to 0.16 at wave 9. Next are Highest Qualification CV_cs, which, again as with CV_us, increase at the highest rate of all covariates, from 0.05 at wave 3 to 0.15 at wave 9. Following this are Ethnicity and Housing Tenure CV_cs: both start at 0.05 at wave 3, then increase to 0.10 and 0.11 respectively at wave 9. Then are Household Composition CV_cs, which increase from 0.04 to 0.07, and Marital Status and Sex CV_cs, which slightly increase from 0.02 at wave 3 to 0.04 and 0.05 respectively at wave 9. Employment Status CV_cs are the smallest of all, and remain fairly stable across waves, only increasing from 0.01 at wave 2 to 0.02 at wave 9.

The COVID-19 Study longitudinal dataset covariate CV_cs are often slightly smaller than the main survey equivalents. They are also smaller than their CV_u counterparts, though all are statistically significantly different from 0, and often for a given covariate increase across waves. The ranking of covariates in terms of impact is comparable to that with CV_us and differs from that in the equivalent main survey datasets. Age CV_cs are the largest and increase from 0.06 at wave 3 to 0.11 at wave 9. Next largest are Highest Qualification and Household Composition CV_cs, which increase from 0.04 at wave 3 to 0.08 and 0.09 respectively at wave 9. Following this, Housing Tenure CV_cs increase from 0.01 at wave 3 to 0.06 at wave 9, Ethnicity and Sex CV_cs increase from 0.02 and 0.03 respectively at wave 3 to 0.05 at wave 9, and Marital Status CV_cs remain stable over waves, at ~0.03. Employment status CV_cs are smallest of all and decrease slightly from 0.03 in wave 3 to 0.02 in wave 4, then remain stable until an increase 0.03 at wave 7, after which they remain the same to wave 9.

The CV_cs for the UKHLS main survey and COVID-19 Study cross-sectional datasets are presented in Appendix B Figure B4 (tabulated values and indicator 95% CIs are presented in Appendix B Table B4). They are of a similar size to those for the longitudinal datasets. Main survey CV_cs are all smaller than their CV_u counterparts, suggesting correlations between covariate impacts, but they are also almost always statistically significantly different from 0 (the exceptions are several Employment Status CV_cs). In addition, for a given covariate they often increase across waves. The ranking of covariates in terms of impact is comparable to that with CV_us and in the main survey longitudinal datasets. Age has the largest CV_cs, which increase from 0.04 at wave 2 to 0.12 at wave 9. Almost as large are the CV_cs for Highest Qualification, which increase from 0.02 at wave 2 to 0.11 at wave 9, and Housing Tenure, which increase from 0.03 at wave 2 to 0.10 at wave 9. Next largest are Ethnicity CV_cs, which increase from 0.03 at wave 2 to 0.07 at wave 9, then CV_cs for Household Composition, which remain around 0.03-0.04 over all waves, then CV_cs for Sex, which increase from 0.01 at wave 2 to 0.04 at wave 9. The smallest CV_cs of all are for Employment Status and Marital Status, which increase from 0.01 at wave 2 to 0.02 at wave 9.

The COVID-19 Study cross-sectional dataset covariate CV_cs are often slightly smaller than main survey equivalents. They are also smaller than their CV_u analogues, though they are almost always statistically significantly different from 0 (the exceptions being some Employment Status and Marital Status CV_cs). CV_c changes across waves vary between covariates. The ranking of covariates in terms of impact is comparable to that with CV_us and in COVID-19 Study longitudinal datasets but differs from that in the main survey cross-sectional datasets. Age has the largest CV_cs, which increase from 0.04 at wave 2 to 0.08 at wave 6, then decrease to 0.04 by wave 9. Next largest are CV_cs for Highest Qualification, Household Composition and Sex, which exhibit decreasing and increasing patterns over waves. The lowest CV_cs for Highest Qualification are at waves 3-4 (0.02) and the highest (0.06) at wave 6. The lowest Household Composition CV_c is at wave 4 (0.01) and the highest (0.05) at waves 6-7, with CV_cs decreasing to 0.03 at wave 8. Sex CV_cs are lowest at waves 2 and 4 (0.02) and highest at waves 6 and 9 (0.04). Following this, Housing Tenure CV_cs increase from 0.01 at wave 2 to 0.03 at wave 7, then decrease to 0.02 at wave 9, Marital status CV_cs increase from 0.02 in wave 2 to 0.03 in wave 4, then decrease to 0.02 by wave 9, and Ethnicity CV_cs remain between 0.01 and 0.02 across all waves. Employment Status CV_cs are the smallest of all, remaining at ~0.01.

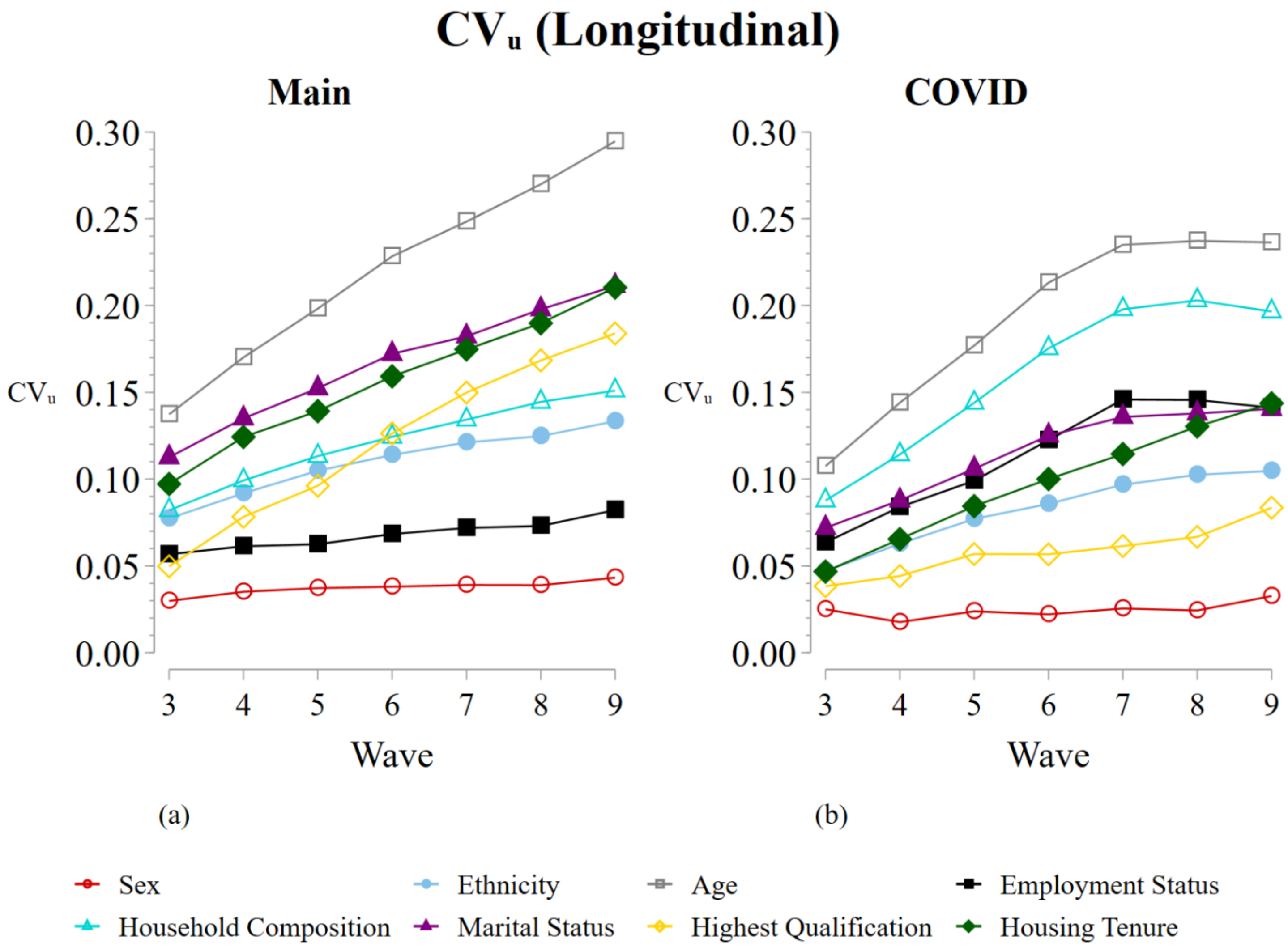


Figure 2.2: Partial CV$_u$s for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

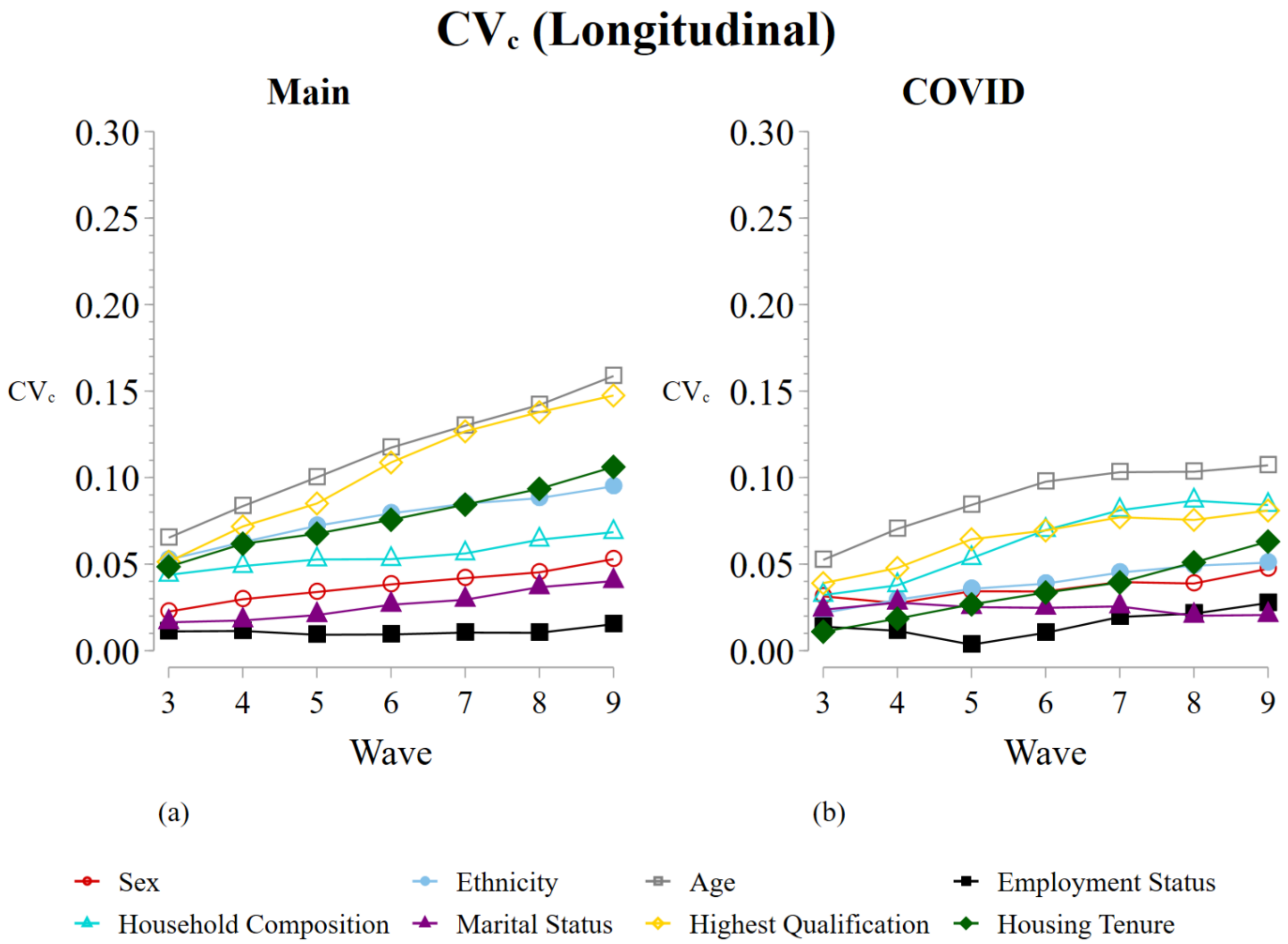


Figure 2.3: Partial CV_cs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

2.3.4. Partial Category CVs

It is not possible to present partial covariate category CVs for all auxiliary covariates due to space constraints. Hence, instead, in the following section such indicators are reported for three important covariates: Age, Highest Qualification, and Housing Tenure.

Partial unconditional category CVs (CV_us) measure univariate associations with response propensity variation. Positive values indicate category over-representation among respondents, and negative values under-representation. Zero values indicate no associated non-representativeness i.e., that respondents are a random subset of the (in this case weighted) eligible sample with respect to the category. UKHLS main survey and COVID-19 Study longitudinal dataset category CV_us for the three mentioned covariates are presented in Figures 2.4, 2.6 and 2.8 (tabulated values for all covariates and indicator 95% CIs are presented in Appendix Table B10). In the main survey, CV_us for main survey Age covariate categories are almost all statistically significant (exceptions are one value each for the 35-44 and 65+ categories), implying non-trivial associated non-representativeness. The 16-19, 20-24 and (least so) 25-34 categories are all increasingly under-represented across waves, and the 35-44 (least so), 45-54 and 55-64 categories increasingly over-represented. The 65+ category is over-represented at wave 3 but becomes under-represented from wave 7. CV_us for Highest Qualification categories are mostly significant (exceptions are at early waves for the category Other). Those with degrees become increasing over-represented across waves, and those with No qualifications increasing under-represented. Those with A-Level, GCSE or Other qualifications are slightly less under-represented than those with No qualifications or become so by wave 9. CV_us for Housing Tenure categories are almost always significant (the sole exception is for the Other category at wave 2). Those who own their accommodation become increasingly over-represented across waves, and those who rent it increasingly under-represented. Those in other types of accommodation are (almost always) slightly under-represented.

In the COVID-19 Study, Age category CV_us are mostly significant (exceptions are for the 35-44 category at wave 3, and most CV_us for the 45-54 category). The 16-19, 20-24 and 25-34 categories all become increasingly under-represented from wave 2 to wave 7, then become slightly less under-represented or stabilise over waves 8 and 9 (as previously mentioned, these patterns are likely to be a consequence of reduced drop-out rates among respondents to all previous waves in response to serology testing and increased financial incentives being offered at waves 8 and 9). The 35-44 category shows the same pattern as the younger age groups, unlike in the main survey, in which it was under-represented. The 54-64 and 65+ categories are increasing over-represented (the differences in pattern with the latter category compared to in the main survey may reflect the shorter time period covered by the COVID-19 Study). The Highest Qualifications covariate category Degree is always similarly and significantly over-represented in the dataset. The other Highest Qualifications covariate categories are significantly under-represented or CV_us are non-significant), with indicators remaining roughly similarly sized across waves. CV_us for Housing Tenure categories follow a pattern comparable to that observed in the main survey. Those who own their accommodation become increasingly significantly over-represented across waves, and those who rent it increasing significantly under-represented. Those in other types of accommodation are not significantly over- or under-represented. In general, COVID-19 Study CV_us are smaller than equivalents for the UKHLS main survey.

Category CV_us for the UKHLS main survey and COVID-19 Study cross-sectional datasets are presented in Appendix B Figures B5, B7, and B9 (tabulated values for all covariates and indicator 95% CIs are presented in Appendix B Table B5). CV_us for main survey covariate Age categories are almost all statistically significant (exceptions are one value each for the 35-44 and 65+ categories), implying non-trivial associated non-representativeness. Similar to with the longitudinal datasets, the 16-19, 20-24 and (least so) 25-34 categories are all increasing under-represented across waves, and the 35-44 (least so), 45-54 and 55-64 categories all increasing over-represented, with the 65+ category beginning as over-represented at wave 2 but becoming under-represented by wave 5. CV_us for Highest Qualification categories Degree and No qualifications are all significant, with the former category increasing over-represented across waves, and the latter increasing under-represented. CV_us for A level, GCSE or Other qualifications categories are either non-significant, or suggest slight under-representation, with patterns uneven so that categories are significant or not depending on wave. CV_us for Housing Tenure categories follow a pattern comparable to that observed in the longitudinal datasets. Those who own their accommodation become increasingly significantly over-represented across waves, and those who rent it increasingly significantly under-represented. Those in other types of accommodation are either slightly over-represented, or CV_us are non-significant).

In the COVID-19 Study cross-sectional datasets, CV_us for Age categories follow a similar pattern to longitudinal dataset equivalents in terms of whether categories are significantly under- or over-represented. It is notable though, that after wave 7, most categories become less under- or over-represented, a pattern that is again likely to be related to reduced respondent drop out and re-engagement with the Study of previous non-respondents due to the serology testing and increased financial incentives offered at waves 8 and 9 (see also section 2.3.1). Again, similar to with the longitudinal datasets, the Highest Qualifications covariate category Degree is always significantly over-represented in the dataset, with CV_us remaining of a similar size across waves. The other Highest Qualifications covariate categories are significantly under-represented, or indicators are non-significant), with CV_us remaining roughly similarly sized across waves. Those with other qualifications, A-Levels, or no qualifications, are slightly under-represented in waves 3-9, waves 8-9 and wave 9 respectively. The CV_us for those with GCSEs are not significant. Concerning the covariate Housing Tenure, those who own their accommodation are significantly over-represented in datasets, and those who rent it significantly under-represented. With both categories, CV_us increase in magnitude slightly from waves 2 to 7, but then decrease at waves 8 and 9. Those in other types of accommodation are neither significantly over- nor under-represented. In general, COVID-19 Study CV_us are smaller than those for the UKHLS main survey.

The partial conditional category CVs (CV_cs) consider multivariate associations with response propensity variation and quantify solely attributable non-representativeness. Larger values indicate greater associated non-representativeness, and zero values no associated non-representativeness i.e., that respondents are a random subset of the (in this case weighted) eligible sample with respect to the category when the effects of the other covariates are accounted for. UKHLS main survey and COVID-19 Study longitudinal dataset category CV_cs for the covariates Age, Highest Qualification and Housing Tenure are presented in Figures 2.5, 2.7 and 2.9 (tabulated values for all covariates and indicator 95% CIs are presented in Appendix B Table B11). In the main survey, CV_cs for Age categories are all statistically significant and increase across waves. CV_cs are largest for the 55-64 category and increase from wave 3 to wave 9. CV_cs for the other categories are smaller, and in some cases rates of increase slow after wave 6. CV_cs for Highest Qualification categories are also all significant and increase across waves, with those for Degree and No Qualifications higher than those for the other categories. CV_cs for Housing Tenure categories are almost always significant (the one exception is for the Other category at wave 4). CV_cs for those who own their accommodation or rent it accommodation increase across waves, while CV_cs for the Other category, although they increase very slightly across waves, do so at a very slow rate.

In the COVID-19 Study, CV_cs for Age categories are always statistically significant. As in the main survey, CV_cs for the 55-64 category are largest. CV_cs for the 65+ category are smallest, with CV_cs for the other categories falling between those for these two categories. Regarding patterns across waves, generally CV_cs increase from waves 3 to 6, then afterwards stabilise. CV_cs for Highest Qualification categories are also always significant. Those for the Other category are largest and increase unevenly from waves 3 to 7 before decreasing slightly. CV_cs for the other categories are similar, and may increase slightly across waves, remain about the same, or even (in the case of the A-Level category) decrease from wave 6 onwards. CV_cs for Housing Tenure categories are almost always significant (the exceptions being those for the Other category). CV_cs for those who own their accommodation or rent it are largest and increase across waves. In general, CV_cs for COVID-19 Study covariate categories are smaller than main survey equivalents.

The UKHLS main survey and COVID-19 Study cross-sectional dataset category CV_cs for the covariates Age, Highest Qualification and Housing Tenure are presented in Appendix Figures B6, B8, and B10 (tabulated indicator values for all covariates and indicator 95% CIs are presented in Appendix B Table B6). CV_cs for Age categories are always statistically significant. Those for the 55-64 category are largest and increase across waves. Those for the other categories are smaller and similar, and also tend to increase across waves. CV_cs for Highest Qualification categories are also always significant. As with the equivalent longitudinal datasets, those for Degree and No Qualifications are higher than those for the other categories, with increases across waves observed in all cases. CV_cs for Housing Tenure categories are almost always significant (the exceptions are several Other category values). CV_cs for those who own their accommodation or rent it are largest and increase across waves. CV_cs for the other category are much smaller and remain about the same across waves.

In the COVID-19 Study, category CV_cs for Age are always statistically significant. CV_cs for the 55-64 category are largest, and those for the 65+ category smallest. CV_cs for the other categories fall between those for these two categories and are similar. Regarding patterns across waves, CV_cs tend to increase to a maximum at wave 5 or 6, then stabilise or decrease. CV_cs for Highest Qualification categories are almost always significant (the exceptions are one value for each of the None and Other categories). The patterns across waves for different categories are uneven, such that no one category is largest or smallest across all waves. At wave 9, the Other category CV_c is slightly larger than those for the other categories, and the CV_c for the A-Level category slightly smaller. CV_cs for Housing Tenure categories are mostly significant (the exception is those for the Other category). For those who own their accommodation, CV_cs increase very slightly from wave 2 to wave 7, then decrease slightly. For those in rented accommodation, they increase slightly from wave 2 to wave 6, then stabilise. In general, CV_cs for COVID-19 Study covariate categories are smaller than those for main survey equivalents.

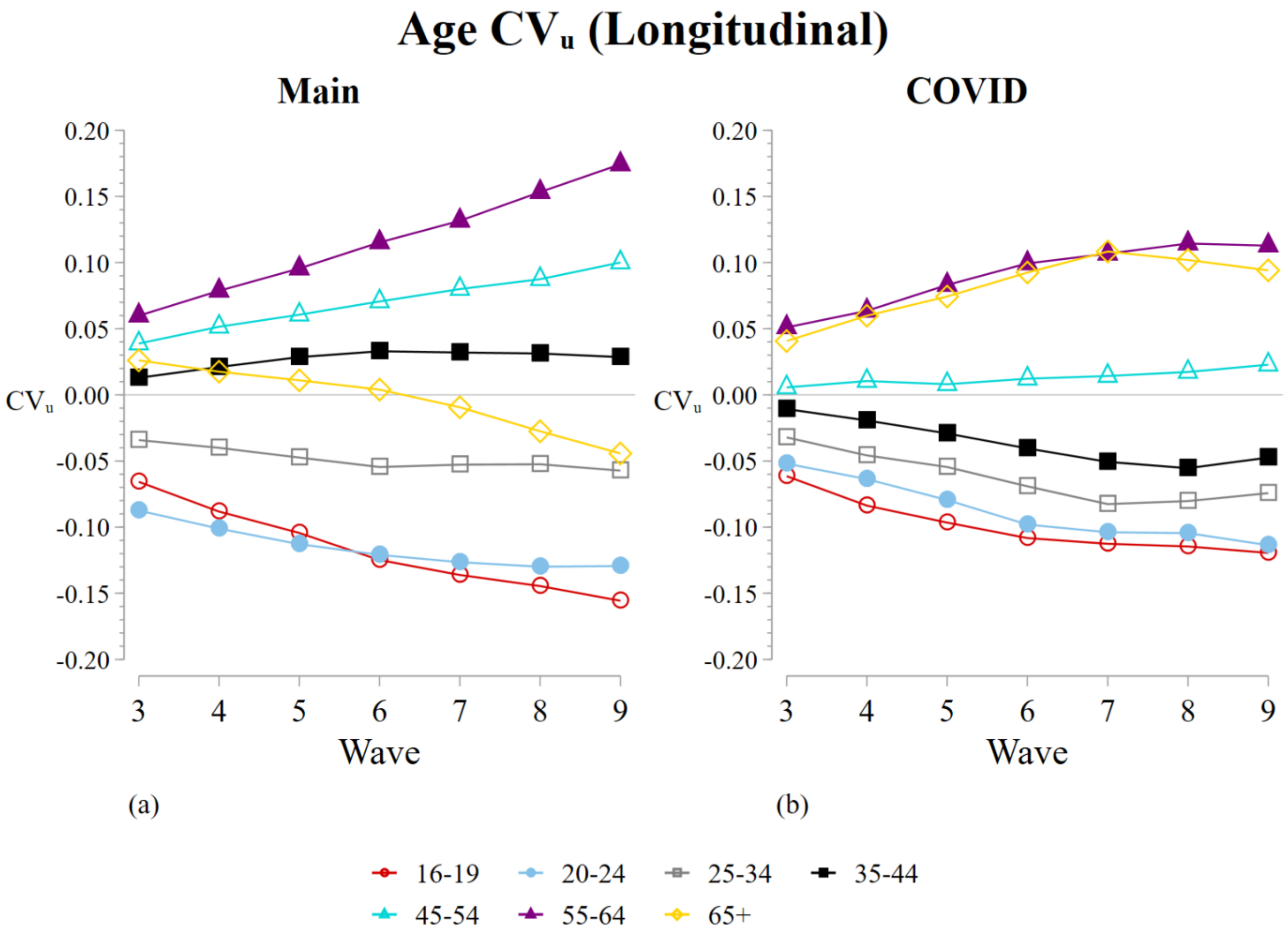


Figure 2.4: Partial category Age CV$_u$s for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

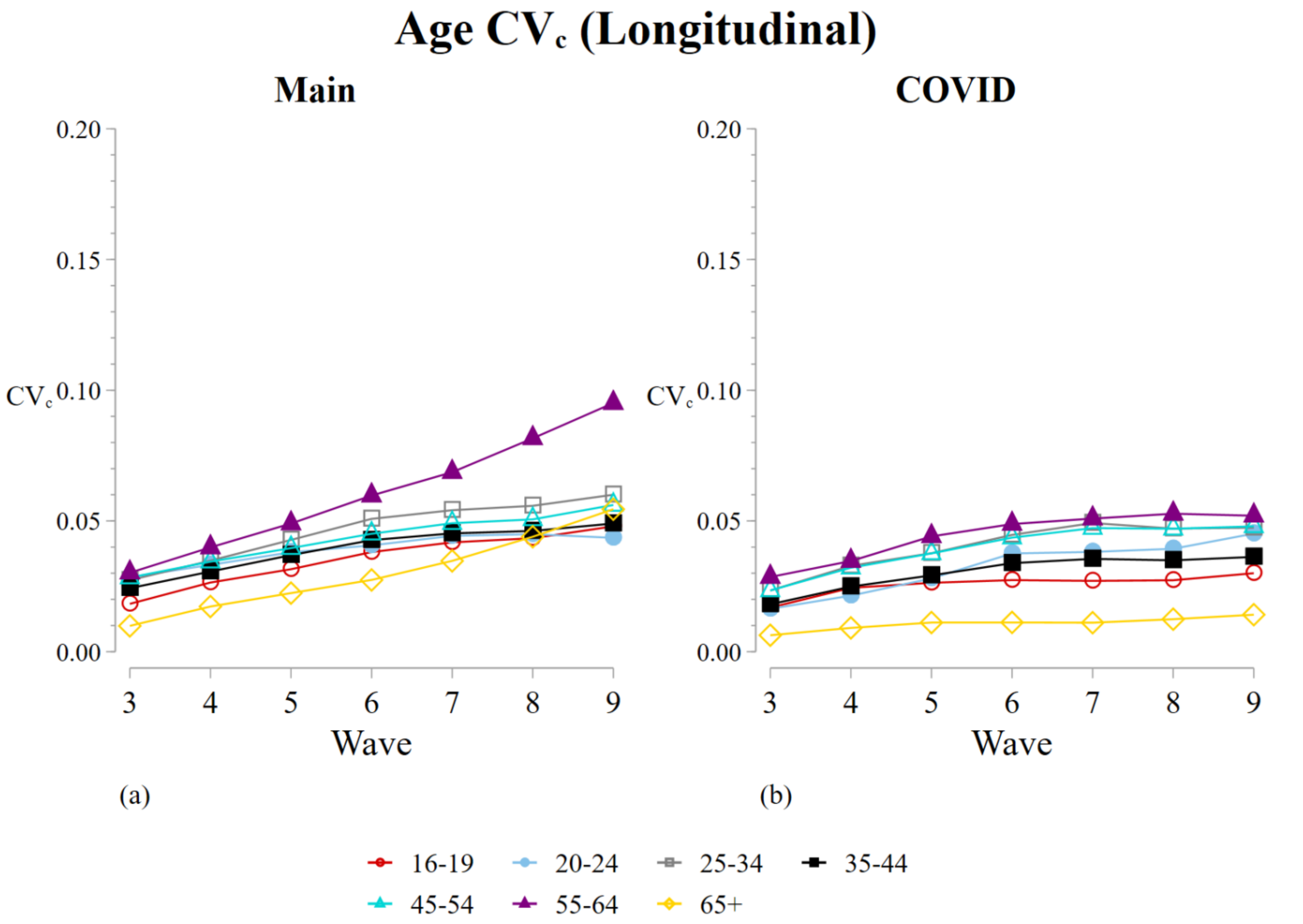


Figure 2.5: Partial category Age CV_cs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

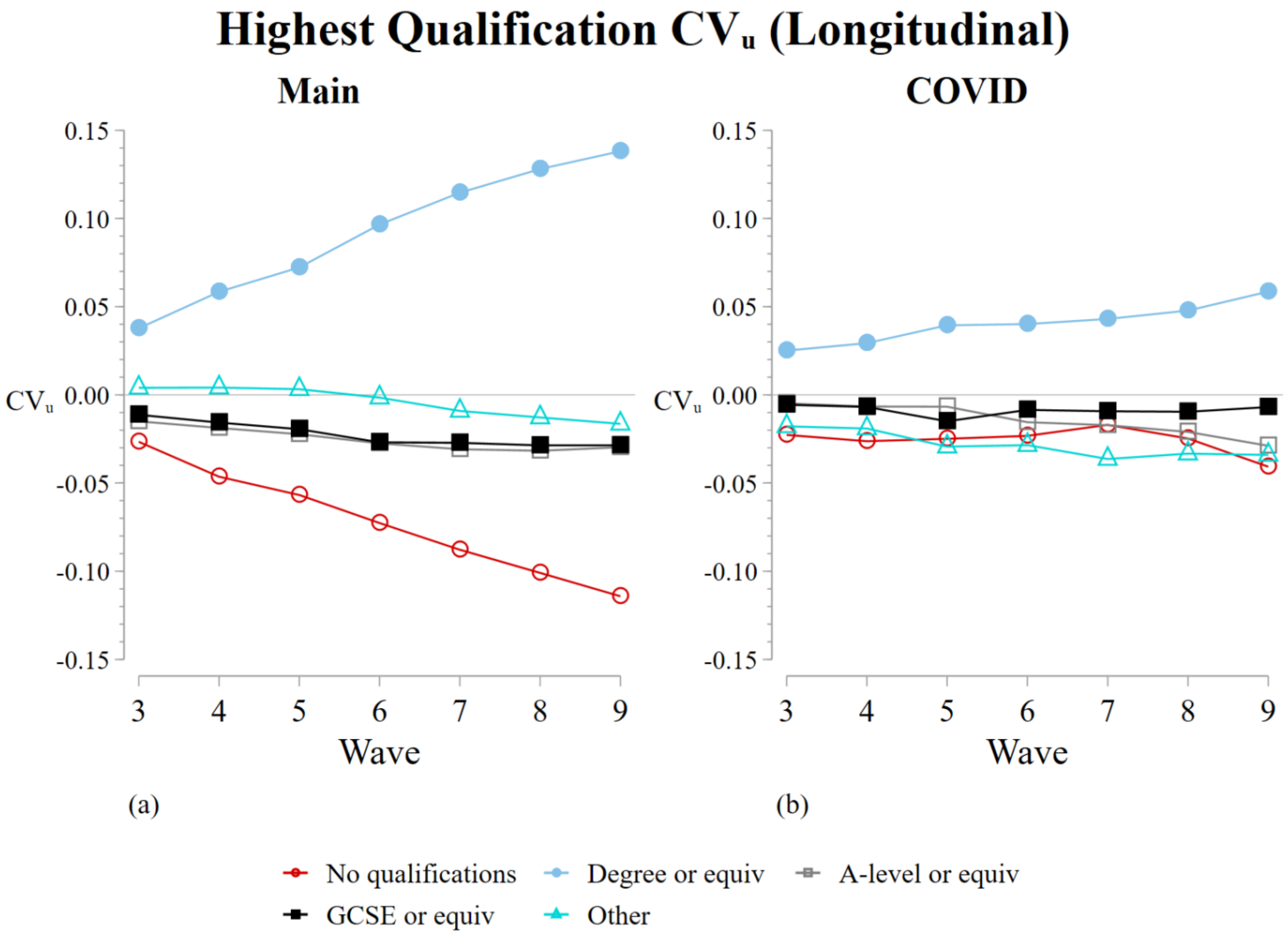


Figure 2.6: Partial category Highest Qualification CV_us for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

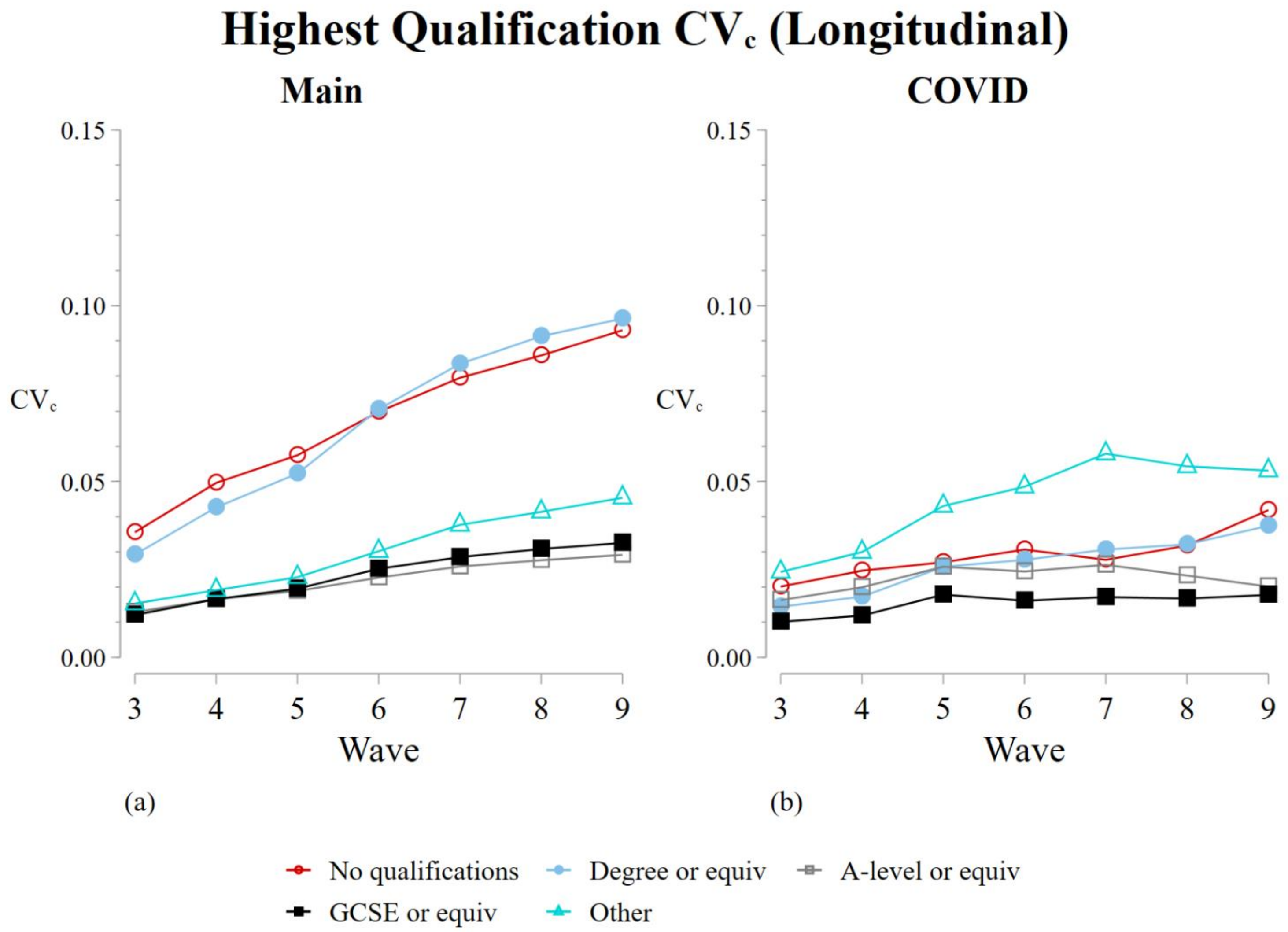


Figure 2.7: Partial category Highest Qualification CV_cs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

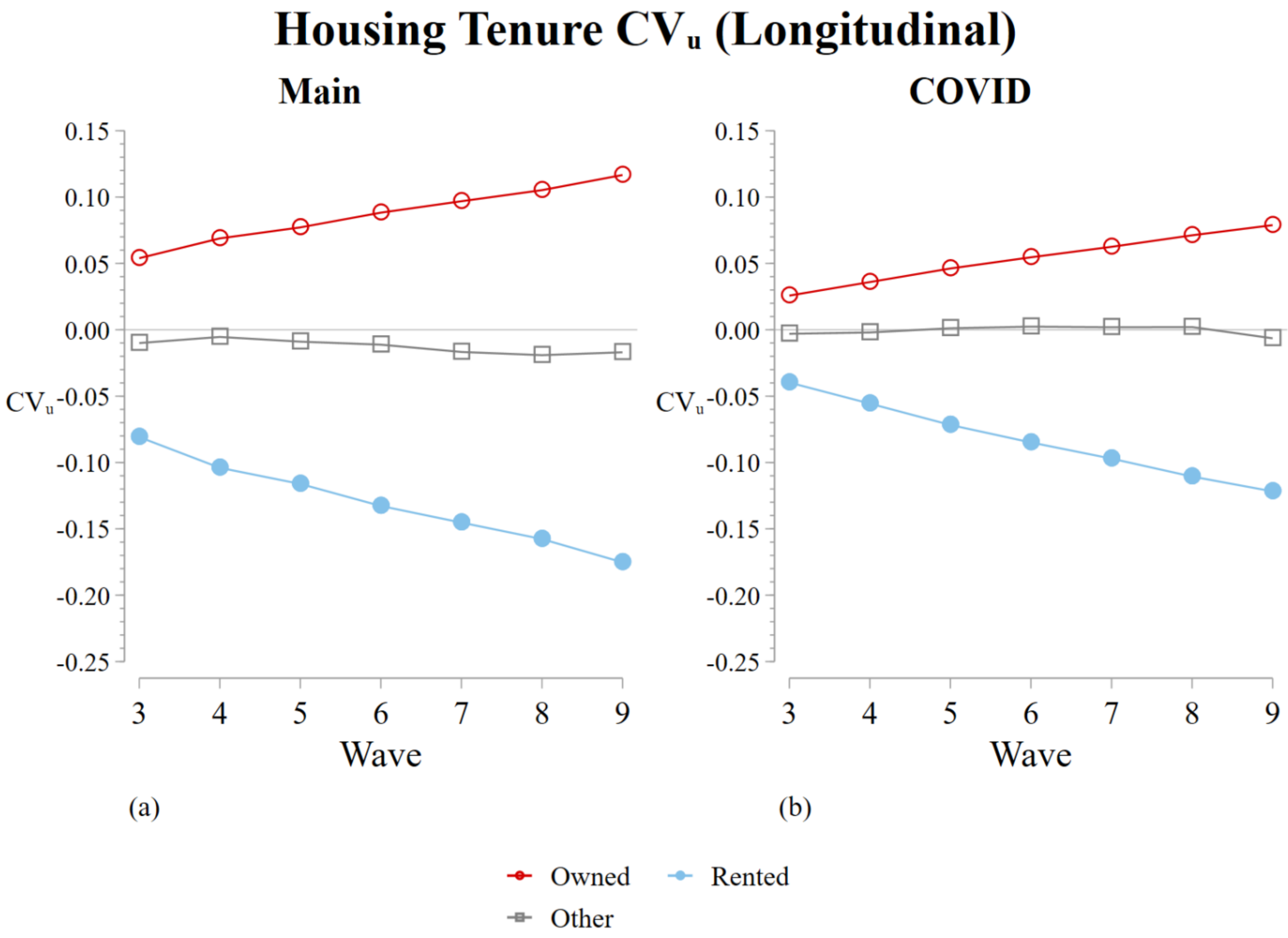


Figure 2.8: Partial category Housing Tenure CV_us for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

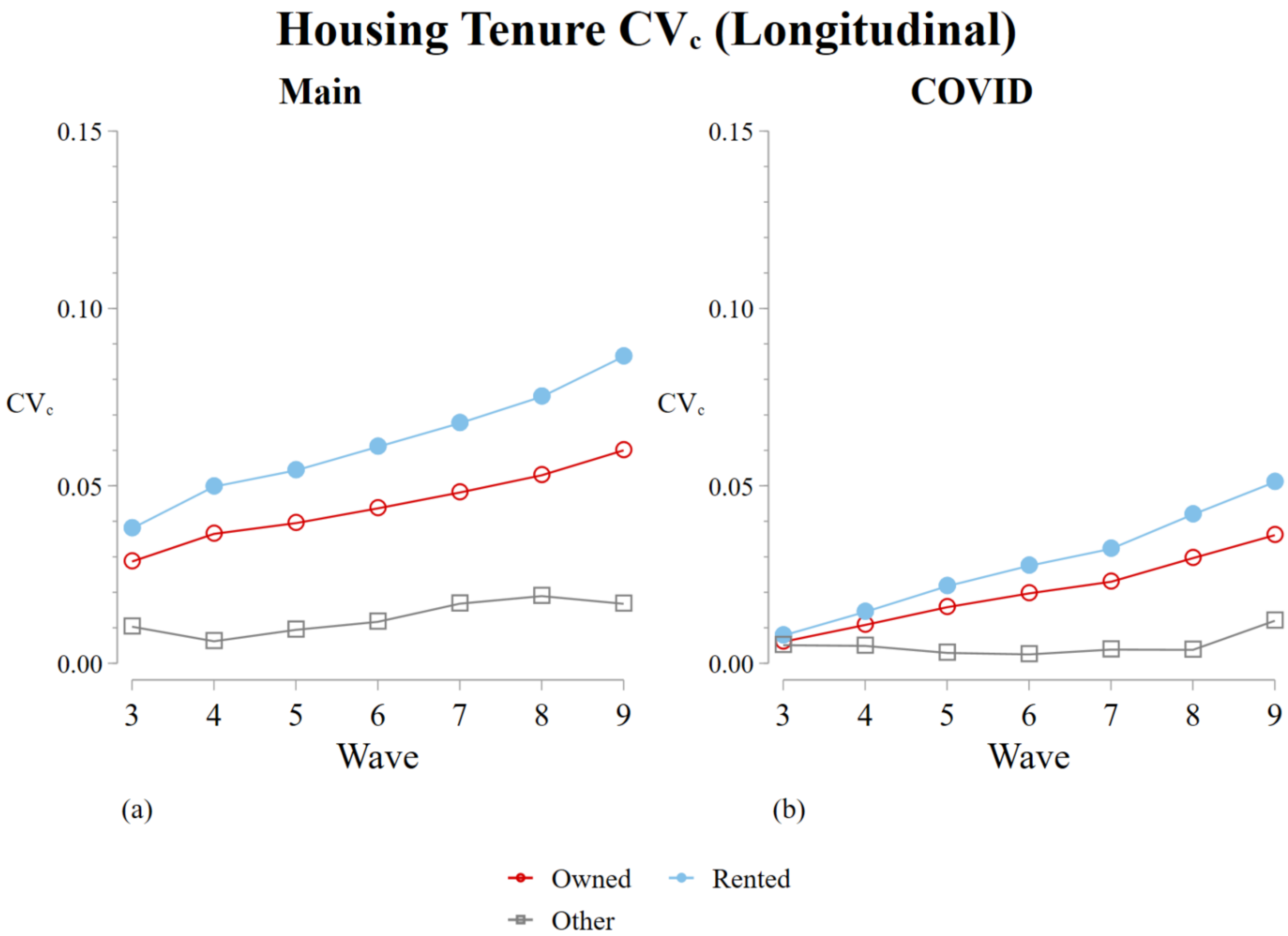


Figure 2.9: Partial category Housing Tenure CV_cs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, longitudinal

2.4 Discussion

This paper evaluated whether dataset quality in terms of likely nonresponse biases and issues impacting on it in the pre-COVID-19 pandemic UKHLS main survey was predictive of similar in the UKHLS COVID-19 Study. The main survey is an annual panel survey that consists of F2F, telephone and web interviews. The COVID-19 Study was fielded to collect information about pandemic impacts at a higher frequency (mostly monthly or bi-monthly) than the main survey. It utilised an eligible sample of main survey participants and was mostly web based due to restrictions aimed at slowing the spread of the virus (for survey details, see Institute for Social and Economic Research (2021b, 2022) and section 2.2.1). Given such differences in frequency and survey mode, the COVID-19 Study was fielded with limited information on how its design was likely to impact on dataset quality (in terms of likely biases) or on quality issues in terms of response propensity variation associated with auxiliary covariates and their categories. The latter are the potential causes of biases, and may be addressable by using bias prevention techniques such as targeted incentives or refreshment samples during data collection (e.g., Groves (2006); Groves et al. (2009); Peytchev et al. (2010); Singer and Ye (2013)) and/or bias adjustment techniques such as nonresponse weights (e.g., Bianchi and Biffignandi (2017); Lynn and Kaminska (2010); Valliant et al. (2018)) after the data collection period.

Both longitudinal datasets including only respondents to the wave in question and all previous waves (the main focus of panel surveys) and cross-sectional datasets including all respondents to the wave were evaluated. Waves 3-9 datasets were considered were for the longitudinal datasets, and waves 2-9 for cross-sectional datasets. The analysis samples consisted of wave 1 respondents (full eligible samples were not used because no information existed on main survey wave 1 non-respondents). Response rates in the two surveys generally decreased across waves, although decreases were smaller in cross-sectional datasets and also rates of decrease slowed (in longitudinal datasets) or rates actually increased (in cross-sectional datasets) at later waves in the COVID-19 Study. Serology (COVID-19 antibody) testing and increased financial incentives to complete the survey were offered at these waves, so the latter pattern was likely due to reduced drop-out among respondents to all previous waves (in longitudinal datasets) and also previous non-respondents re-engaging with the Study (in cross-sectional datasets). Rates were also higher in cross-sectional than longitudinal datasets, due to the less restrictive inclusion criteria. In addition, they were higher in the COVID-19 Study than the main survey. The latter result may somewhat be due to the duration of the COVID-19 Study (18 months) compared to the studied main survey waves (9 years): rates were higher across all waves. But more importantly, it may also reflect the Study's eligible sample consisting of long-term main survey respondents who were likely to be positively disposed towards it, and/or participants who had more time to complete surveys due to the lockdown restrictions in the UK to slow the spread of the virus and/or who responded to the gravity of the situation.

To evaluate likely nonresponse biases, representativeness indicators were used (de Heij et al., 2015; Moore et al., 2018, 2021; Schouten et al., 2012; Schouten et al., 2009; Shlomo & Schouten, 2013; Shlomo et al., 2012). These measure how well respondents reflect the sample by quantifying variation in response propensities estimated using auxiliary covariates available for all sample members. Low propensity variation suggests that respondents are a random subset of the sample with respect to auxiliary covariate values i.e. are representative of the sample., This implies low biases whether or not post data collection bias adjustments to improve quality are computed, since the effectiveness of such techniques increases with dataset representativeness (Moore et al., forthcoming; Schouten et al., 2016). Partial indicators also exist that decompose propensity variation into that associated with auxiliary covariates and their categories. These respectively identify covariates for inclusion in models underlying bias adjustments, and under-represented sub-groups that to similarly improve dataset quality can be targeted by bias prevention techniques during data collection. In addition, approximate indicator standard errors are available, which enable statistical inference when converted into 95% CIs. Specifically, Coefficients of Variation of the Response Propensities (CVs) were used, which standardise propensity variation by its mean, enabling datasets with different response rates to be compared (see also section 2.2.2). In addition, the overall CV, which measures overall dataset quality, predicts the maximal absolute standardised nonresponse bias of survey estimate means.

For the main survey, eight auxiliary covariates (sex, ethnicity, age, employment status, household composition, marital status, highest qualification and housing tenure) from main survey wave 1 were used, with nonresponse weights from the same wave applied to map analysis sample members to their eligible sample (and putatively the UK population at these time points, March 2009-January 2011 for the main sample and June 2019 for the COVID-19 Study sample: see section 2.2.3 for detailed discussion). For the COVID-19 Study, similar main survey wave 9 (the last wave before the pandemic) covariates were used, with the Study wave 1 nonresponse weights applied. Overall CVs implied that all datasets were non-trivially (significantly) non-representative i.e., that they were a non-random subset of the (weighted) analysis sample with respect to auxiliary covariate values. Representativeness mostly decreased across waves, implying that respondents became less random subsets of the (weighted) analysis sample with respect to auxiliary covariate values, although in the COVID-19 Study decreases slowed in the waves 8 and 9 longitudinal datasets and representativeness increased in similar cross-sectional datasets. The latter was likely again due to serology testing and financial incentives being offered and its impact on dropout rates among respondents to all previous waves and previous nonrespondents re-engaging with the survey. Cross-sectional datasets were more representative than longitudinal datasets, implying that all respondents to a wave were more random subsets of the (weighted) analysis sample with respect to auxiliary covariate values than only respondents to the wave and all waves previous. In addition, COVID-19 Study datasets were more representative (more random subsets of the weighted analysis sample) than main survey datasets, likely due to similar reasons to those put forward for the higher Study response rates.

Two types of covariate and category covariate CVs were computed. Unconditional CVs (CV_us) quantify univariate associations between considered covariates (categories) and response propensity variation i.e., the extent to which respondents are a non-random subset of the (weighted) analysis sample with respect to values of the covariate (category). Conditional CVs (CV_cs) quantify the same multivariate associations i.e., the extent to which respondents are a non-random subset of the (weighted) eligible sample with respect to values of the covariate (category) when the impacts of the other covariates are accounted for. CV_cs are used to test whether univariate associations are actually due to correlations between covariates and categories, and therefore are useful for ensuring efficient bias adjustments and targeting of under-represented sub-groups (see also section 2.2.2). In all datasets, covariate CV_us implied non-trivial non-representativeness associated with each of the eight covariates in indicator response propensity models. In most cases, this remained when CV_cs were computed. Both indicators tended to increase across waves, implying that respondents became less random with respect to values of focal covariates, although, similar to with overall CVs, in the COVID-19 Study they often stabilised (in longitudinal datasets) and decreased (in cross-sectional datasets) at waves 8 and 9. Similar to overall CVs, they were slightly smaller in the COVID-19 Study than main survey datasets, and in cross-sectional than longitudinal datasets. Though comparable in longitudinal and cross-sectional datasets, the ranking of covariate impacts also differed between surveys, a topic that is returned to below.

Category CVs for the covariates Age, Highest Qualification and Housing Tenure were focused on in the paper (see the Appendix for CVs for the remaining covariates). CV_u changes across waves were comparable in longitudinal and cross-sectional datasets, but differences existed between surveys. With all covariates, category representativeness again often decreased across waves in the main survey but stabilised or increased at waves 8 and 9 of the COVID-19 Study. Beyond this, with Age in the main survey the 35-44 category was over-represented and the 65+ category went from being over- to under-represented, whereas in the COVID-19 Study the two categories were respectively under- and over-represented. The Highest Qualification No qualifications category was increasingly under-represented in the main survey, but only slightly so in the COVID-19 Study. Housing Tenure category CV_us were comparable in the two surveys. Indicators were slightly smaller in in cross-sectional than longitudinal datasets, and in the COVID-19 Study datasets than main survey datasets. Analogous patterns existed with CV_cs.

These differences in category CVs drive the between survey differences in the ranking of covariate impacts on representativeness mentioned previously. Likely reasons for four of them are given below. They can be grouped into two categories that are probably also relevant for the reasons for the others: those linked to the respective survey designs, and those linked to changes in living conditions during the pandemic. In the first category, the stabilisation of and increases in representativeness in the COVID-19 Study waves 8 and 9, in contrast to the mostly continued decreases in the main survey, was likely due to the aforementioned serology testing and financial incentives offered. In a similar vein, the Age category 65+ was under-represented at later waves of the main survey but over-represented in the COVID-19 Study was likely due to 9 years of accumulated mortality among main survey sample members, whereas the duration of the COVID-19 Study was only 18 months. In the second category, the Highest Qualification category No Qualification was less under-represented in the COVID-19 Study was likely due to members being furloughed from their jobs during parts of the pandemic and having more time to participate in the survey. In addition, the Age 35-44 category was over-represented in the main survey but under-represented in the COVID-19 Study may reflect school closures during parts of the pandemic, which would have reduced the time parents had to participate in the survey due to needing to supervise children (a similar pattern also existed with the Household Composition category Couple with Children: see Appendix B).

A limitation of this research is that actual survey estimate nonresponse biases were not quantified because relevant population values were not available (though this is generally the case for research of this type, see Hand et al. (2018) for discussion). Beyond this though, its findings imply that dataset quality in terms of likely nonresponse biases and issues impacting on it in the pre-pandemic UKHLS main survey did not predict similar in the COVID-19 Study. This is unsurprising given the changes in survey design in terms of data collection frequency and interview mode(s) and the changes in living conditions that were a consequence of the COVID-19 pandemic but has not previously been shown. It is emphasised that this does not mean that the COVID-19 Study datasets were of poor quality: indeed, the findings suggest they were more representative of their weighted analysis sample than in the main survey (equally, the main survey has previously been shown to support high quality inferences (Benzeval et al., 2020)). Rather, it means that the main survey was of limited value for informing on COVID-19 Study dataset quality. This is with respect to both overall quality patterns and response propensity variation associated with auxiliary covariates/categories: the potential cause of biases. The latter is especially of note as it suggests that if bias prevention or adjustment techniques developed to improve datasets in light of such issues in the main survey had been utilised in the COVID-19 Study, their outcomes may have differed. Fortunately, this was not the case, with custom bias prevention (telephone sampling of web survey non-respondents at several waves, which was not studied here, see also section 2.2.1) and adjustment (newly developed, empirically evaluated nonresponse weights, see Moore et al. (forthcoming)) techniques instead being used in the Study.

These findings are important despite the end of the COVID-19 pandemic and the COVID-19 Study. Other pandemics may occur in future and lead to a demand for similar new surveys. In addition, the primary design difference between the surveys, the shift to web mode, was already occurring in the main survey, albeit at a slower pace and not to the same extent (Institute for Social and Economic Research, 2022). Web interviewing has been shown to reach a wider range of sample members, have faster turnaround times, and has lower financial costs than F2F interviewing (Bethlehem, 2008; Couper, 2000; Jäckle et al., 2015; Knoef & de Vos, 2009; Scherpenzeel, 2011). Therefore, it is not inconceivable that one day it may completely replace F2F interviews in the main survey as well (although currently there are no plans to do so). Should either of these events occur, the findings imply that targeted research will be needed to properly predict effects on dataset quality and issues impacting on it.

The findings also have relevance beyond the two UKHLS surveys evaluated. Both in the UK and elsewhere, other new surveys were fielded in response to the COVID-19 pandemic (e.g. Blom et al. (2020); Brown et al. (2021); Burton et al. (2020); Gummer et al. (2020)). These were often derived from existing surveys and subject to increased data collection frequencies and survey mode restrictions, and fielded with limited information on how design changes would impact on dataset quality. In addition, the shift towards an increase in web interviewing outside of the pandemic context is universal (Bianchi et al., 2017; Burton & Jäckle, 2020; Cornesse & Bosnjak, 2018; Couper et al., 2007; Institute for Social and Economic Research, 2022; Nicolaas et al., 2014). Consequently, that in such situations information from existing surveys is likely to be of limited use for predicting dataset quality in terms of nonresponse biases and issues impacting on it should be of broad interest to survey designers. It should also be noted though, that the findings in this paper are unlikely to be of use for making more specific predictions about other surveys. The representativeness indicators used to evaluate dataset quality in the surveys considered here depend on the auxiliary covariates used to model response propensities (Schouten et al., 2012; Schouten et al., 2009). Response propensity correlates can differ both between different surveys in the same country and between countries, and even when commonalities exist, the signs of associations can vary (Behr et al., 2005; Luiten et al., 2020). Therefore, as also stressed with the UKHLS surveys (see previous paragraph), in these surveys targeted research will be needed to predict the effects of design changes on survey dataset quality and issues impacting on it.

3. Rising 16s: Does youth survey response predict young adult survey response?

Abstract

Although young adults (aged 16-25) are more likely to attrite than older sample members, reducing survey dataset sizes and potentially causing nonresponse biases (survey estimate deviations from population values), little is known about their survey response behaviour. To understand how to encourage them to participate more in surveys, this paper investigates the correlates of attrition among such individuals in *Understanding Society*: the UK Household Longitudinal Study (UKHLS). In this survey, sample members are enumerated from birth and are eligible to complete the youth survey from age 10 and the adult survey from age 16, so that there is up to six years' worth of youth questionnaire and response pattern data before they join the adult sample. Given this, this research identifies patterns of youth survey response, then uses this to evaluate whether such behaviour, along with parental influences (a potential important factor in determining the behaviour of considered sample members) can predict young adult survey response behaviour. The implications of the findings of this research for intervention strategies designed to improve survey response among young adults are then discussed.

Keywords: youth survey response, response patterns, attrition, panel surveys, latent class analysis

3.1 Introduction

The purpose of a general population panel survey is to adequately represent a study population (such as, a country) over time so that societal trends can be studied. One of the main difficulties in doing so is panel attrition, which can be defined as the inevitable loss of sample members, through failure to lo cate or contact them , or their refusal to participate in the survey (Uhrig, 2008). While panel attrition reduces the survey sample size resulting in the reduced precision of survey estimates, if the attrition is random, it is not entirely problematic (Groves et al., 2009). However, if some population sub-groups are more likely to attrite than others, it can cause nonresponse biases (survey estimate deviations from the study population values), which in turn can cause invalid inferences (Groves et al., 2009). Two sub-groups of concern in this context are children (those under the age of 18) and young people (18-24). In most studies of attrition, age is a significant predictor with younger people tending to attrite more than their older counterparts (Lipps, 2009; Lynn & Borkowska, 2018; Uhrig, 2008; Watson & Wooden, 2009). This is an issue for panel surveys as their utility lies in repeated measures for the same individuals to ensure there is a wealth of data to study gross change (Lynn, 2009a). As such, the continued participation of younger sample members is important. Despite this however, there is a limited amount of methodological research that focuses on children and young survey members, especially in general population surveys (Omrani et al., 2019).

3.1.1 Recruitment and Retention of Children and Young People

In the past, survey data concerning children was generally collected in proxy form from a responsible adult (e.g., parents or guardians). In some surveys, this is still the case, whether that be the whole survey or partially, with in the latter case some questions asked of the responsible adult and some asked of the child (Scott, 1997, 2008). Collecting data directly from the child can improve data quality (Fuchs, 2005). However, interviewing children requires special attention due to ethical concerns (such as, assent, consent and privacy) and changes in cognitive functioning which can affect the ability to understand and respond to survey questions and in turn, harm survey data quality (Borgers et al., 2000; Mavletova & Lynn, 2019; Omrani et al., 2019).

Adolescent respondents (aged 10-19) in particular have high levels of attrition, and surveys find that transitioning from a responsible adult primarily answering the questions to the adolescent answering contributes to this attrition (Calderwood et al., 2015). It is also argued that attrition in young people is high because they are less likely to have housing stability and more likely to be students and work in jobs with unconventional hours, which makes it difficult for interviewers to locate and contact them (Lynn, 2020; Lynn et al., 2012; Uhrig, 2008). This contributes to the challenges survey managers face when recruiting "new" adults to take part in the adult survey for the first time, so more knowledge about how to encourage these types of respondents is required.

As mentioned previously, in household panels, it is important to retain sample members where possible. However, the way in which sample members respond is not always linear. It is not always as straight forward as responding at every single wave or dropping out permanently since some respondents miss waves but then start responding i.e., they may respond intermittently. As such, two important mechanisms in understanding nonresponse are "commitment" and "habit" (Lugtig, 2014). Commitment refers to the value respondents place on the study, which can lead to continued participation. Moreover, a habit is formed when respondents repeatedly participate in a survey resulting in them not having to think about the decision to participate and as such, nonresponse can be used as an indicator for future attrition (Lugtig, 2014). However, another mechanism is shock, which may lead to sudden dropout. Examples of this are illness, death, and situational changes, such as moving house, changes in household composition (Lugtig, 2014). With this in mind, it is clear that retaining children and young people in household panels is important because they can potentially be encouraged to commit to participating in the study and form this "habit" from a young age and thus, continue participating for as long as possible. Though, it must be noted that young people in particular are in a transitional part of the life course, i.e., leaving the parental home and transitioning from full-time education to university or the workforce, which may make it difficult for high commitment and habits to be formed. Hence, understanding how children and young people respond should contribute to understanding how they respond in adulthood.

Despite the limited amount of methodological research concerning children and younger sample members in general population surveys, findings from other types of surveys, such as cohort studies and youth-specific studies, can be informative. Silverwood et al. (2020) analysed predictors of nonresponse using the Next Steps cohort study, which sampled children in schools at age 13-14 (Calderwood et al., 2021). Silverwood et al. (2020) were interested in whether sample members responded at wave 8 (aged 25-26). Findings suggested that the strongest predictor was nonresponse at previous waves. Additionally, male sample members, those who moved house or lived in rented housing, those with behavioural problems at school, younger parents, and those no longer in full time education in later waves were just some of the indicators of nonresponse identified. In addition to the predictors mentioned, other cohort or youth-specific longitudinal studies have identified ethnic minority sample members. low household income, low parental education, as important predictors (Eisner et al., 2019; Hawkes & Plewis, 2006; Post et al., 2012; Rothman, 2009; Winding et al., 2014).

3.1.2 Parental Influence on Youth Participation

In general, studies have shown that sample members are influenced to participate in surveys by other participating household members, with the opposite effect observed for nonresponding households (Watson & Wooden, 2009, 2014). As children grow up and become teenagers, they tend to be given more freedom by their parent and guardians with regard to decision making, such as in their education, part-time jobs and hobbies which may impact their futures (Calderwood et al., 2015). Despite this, as they are still legally minors and parents and guardians still remain influential so the latter can be considered as gatekeepers when trying to gain interviews. Parents may encourage their children to participate in social research that the children do not want to participate in, but equally they may do the opposite, dissuading their children from participating (Coyne, 2010). Some parents may also assume the decision-maker role in their children's participation in research without their children being aware that they could decide for themselves (Coyne, 2010; Ireland & Holloway, 1996). In addition to this, many household surveys focus on the adult, so the children's responses can be conditional on an adult in the household also responding. The same can be said for young adult respondents who live with their parents. Such issues pose a difficulty for household surveys, such as UKHLS, where every person in the household is encouraged to participate.

3.1.3 Research Questions

As noted in the previous sections, there are substantial gaps in our knowledge concerning survey participation and attrition in young people. Attrition rates among such individuals are high, especially as they transition into adulthood, which is detrimental to the quality of panel surveys, whose utility relies on repeated measurements of sample members. To address these knowledge gaps, this paper examines youth response behaviour in *Understanding Society:*

the UK Household Longitudinal Study (UKHLS), a large longitudinal survey of UK population members (Institute for Social and Economic Research, 2022; University of Essex & Institute for Social and Economic Research, 2022). Specifically, the research questions addressed are:

1. Can survey response behaviour in youths predict subsequent survey response behaviour as a young adult?
2. How important is parental influence in predicting youths' response behaviour as a young adult?

Since response behaviour in panel surveys is not necessarily linear and can follow various patterns (see section 3.1.1), latent class analysis (LCA) is used to address the aforementioned research questions. LCA enables individuals to be categorised into classes based on their response patterns (Collins & Lanza, 2010), and is used here to classify patterns of youth response. Then, logistic regression methods are used to estimate the log odds of these classes responding once transitioned to the adult survey, along with other correlates of the latter. The findings of this research will provide insight into the issues of youth attrition, recruitment, and retention in panel surveys. In addition, the findings will serve as foundation for further research into the recruitment of young sample members into adult surveys, and can be used to inform survey management participant liaison decisions (Davis-Kean et al., 2018). This paper proceeds as follows. First in section 3.2, the UKHLS survey is described, and the analysis methods are outlined. Second, the analysis results are reported in section 3.3. Finally, the implications of these findings for survey design are discussed in section 3.4.

3.2 Methods

3.2.1 Data

This research uses the UK's only nationally representative household panel study, *Understanding Society*: the UK Household Longitudinal Study (UKHLS) which began with a sample of 40,000 UK households in 2009. The UKHLS sample also includes households from its predecessor survey the British Household Panel Survey (BHPS), which ran from 1991 to 2008, achieving 18 waves of data. The UKHLS aims to enumerate every member of the household annually and follow these sample members over time. Sample members who have previously been enumerated but move out of their original household are followed as long as they remain in the scope of the survey (i.e., remaining in the UK). Once enumerated, one sample member in the household is asked to complete a household interview. Then, sample members are asked to complete adult or youth individual interviews. Initially, all interviews were face-to-face (F2F), but from wave 3, a small amount of telephone interviews were offered. In wave 7, web interviews were introduced, with the proportion of such interviews issued increasing each year since (Institute for Social and Economic Research, 2022).

If an adult in the household is responsible for a child (aged 0+), they are also asked questions about the child. The topics covered include child development, childcare, and schools. Additionally, following its predecessor survey, the BHPS (the first household panel study in Europe to interview such sample members in 1994), the UKHLS interviews sample members aged 10-15 (Mavletova & Lynn, 2017). The youth interview is paper self-completion, with an average completion time of 10 minutes. The questionnaire is given with parental permission in an F2F interview and sent by post if the household completed web interviews (Institute for Social and Economic Research, 2022). This survey design makes UKHLS a useful resource to answer the research questions addressed in this paper, as it has rich household data and includes children and young people in the interviews.

I use pooled data from wave 1 to wave 12 of UKHLS and the sample contains 12,171 Original Sample Members who were enumerated into the study before the age of 16 and turned 16 while in the study (University of Essex & Institute for Social and Economic Research, 2022).

3.2.2 Repeated Measures Latent Class Analysis

Latent class analysis (LCA) is the chosen analysis method for this study as the models include observed categorical variables, which measure unobserved latent categorical variables, in this case, youth response behaviour. These models assume that these observed variables are independent and it is the latent variable that explains the relationship between the observed variables and this is termed local independence (Collins & Lanza, 2010). These observations are grouped into meaningful categories (termed “classes”) based on their similarities. More specifically, Repeated Measures LCA (RMLCA) is used. This method allows the incorporation of observed categorical variables that are the same but measured at different timepoints, such as age (Collins & Lanza, 2010). In this study, there were six observed binary variables, signifying whether the sample member had completed a youth interview between ages 10 and 15 and there are no missing values.

RMLCA involves estimating various models and determining the model with the best fit. Each model was estimated with a specified number of classes and the models were nested, such that the next model generated was estimated with an additional class compared to the previous model. The deviance, Bayesian information criterion (BIC), entropy and bootstrapped likelihood ratio test (BLRT) are just some statistics that can be used to evaluate the models to determine the model with the best fit. The deviance and BLRT are statistics used to evaluate nested models and cannot be interpreted in isolation, for both statistics, one must compare the value with the previous model. Lower values indicate better fitting models for the deviance and the BLRT value shows whether the model significantly improves the fit compared to the previous (Kim, 2014; Lugtig, 2014; Singer & Willett, 2003). Entropy highlights the class separation in the model and values above 0.8 signify that observations can be accurately assigned to one class (Lugtig, 2014). In addition to these quantitative methods of evaluation, there is also the subjective interpretation of the classes, whether one can derive meaningful explanations for each class. Therefore, the main objective is to select a model that contains classes that can be understood in the relation to the data and that has high class separation. The RMLCA models were estimated in Latent GOLD 6 (Statistical Innovations Inc., 2021).

3.2.3 Logistic Regression Analyses

While RMLCA is useful in identifying meaningful classes of observations, further analyses are needed to examine how the class membership relates to other covariates of interest. Specifically, logistic regression is used to determine whether the youth response (estimated using LCA) can predict early adulthood response. This can be done using the three-step approach which involves first estimating the latent class model then assigning the observations to the latent classes before finally, estimating how the classification values are related to the covariates of interest (Bakk et al., 2013; Vermunt, 2010). However, classification error is an issue that must be addressed as observations cannot be placed into classes with complete certainty. Classification error is also related to entropy (the class separation indicator) as lower levels of entropy would lead to higher levels of classification error (Heron et al., 2015). The modified Bolck-Croon-Hagenaars (BCH) approach accounts for this and it 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 RMLCA analyses can be used as a weight in further analyses (Bakk et al., 2013; Vermunt, 2010).

Table 3.1: Descriptive statistics for whether the respondent completed an interview

Whether respondent completed an interview	% of sample	Of those with an interview…		
		% of Female Respondents	% of Ethnic Minority Respondents	% of Respondents living with parents between ages 16-25
First full adult interview at age 16	47	52	26	71
At least 1 full adult interview between ages 16-19	57	52	27	71
At least 1 full adult interview between ages 16-25	58	52	27	71
80% of eligible adult interviews completed between ages 16-25	23	57	24	81
At least 1 full adult interview between ages 17-19 (but not age 16)	10	49	33	70
At least 1 full adult interview between ages 20-25 (but not between ages 16-19)	0.8	46	30	62

Table 3.1 shows the different compositions for whether a respondent completed an adult interview, given the respondent already being in the sample before age 16. 57% of the sample completed at least 1 full interview in the first four years of being eligible to participate in an adult survey. 58% of the sample completed at least 1 full interview in the first 10 years, only a 1% increase from ages 20-25. Moreover, only 10% of the sample completed at least 1 full interview between 17-19 but not age 16. This shows that whether sample members respond at age 16 (i.e., the first adult interview) is a good indicator of whether they will respond in early adulthood. Additionally, this table shows the importance of living in the same household as parents, for those who completed at least one full interview in early adulthood, 71% lived

with at least 1 parent in these 10 years. The percentages of female and ethnic minority respondents are quite similar for those who completed an interview between 16-25 (52-57% female; 24-27% ethnic minority) but slightly different for those who had at least one interview but not in the first few years (46-49% female; 30-33% ethnic minority).

Given the above, logistic regression models were estimated using three dependent variables (1) whether or not the sample member completed their first full adult individual interview at age 16, (2) whether or not the sample member completed at least one full adult individual interview aged 16-19, (3) whether or not the sample member completed at least 80% of the eligible full adult individual interviews between ages 16-25. In the results section, average marginal effects estimated from the logistic regression models are presented so the findings can be better interpreted and compared.

The independent variables in the models include the assigned class from the RMLCA, covariates collected during the youth years (sex, ethnicity, household mode, household composition and household income), and covariates related to parents (parental response and living with parents in early adulthood) (see Appendix C Table C1 for UKHLS specific variable names). As it is well known that the mode of data collection can affect response rates (see Bianchi et al. (2017); Lynn (2011a)), the categorical variable for household mode was included and it measures the proportion of eligible household interviews completed by web during the sample member's six youth years (ages 10-15). This was included to account for the difference in interview experience with the web mode, for example, no in-person interviewer and a lower likelihood all interviews are completed around the same time. Therefore, web interviews may give respondents more opportunities to complete the interview. As the web interviews only started from wave 7, prior to that respondents would not have been eligible, so this is also included as a category, in addition to less than half completed by web, half or more completed by web and all completed by web. The reference category is none completed by web. Household composition is the average household composition reported in youth years. The average household income is the average across reported waves adjusted using the modified OECD equivalence scale to enable comparison of households of different sizes and compositions and by the retail price index so that it can be accurately compared across time (Canberra Group, 2011; Fisher et al., 2019; ONS, 2022).

Parental response is a variable that measured whether the respondent's parent(s) had completed at least 80% of their eligible individual interviews. If the respondent had two parents listed, the average of the two was used. The second parental measure is whether the sample member lived in the same household with at least one parent (biological, adoptive, step or foster) in eligible waves in early adulthood (aged 16-25). This was included in a separate set of models as the measure was conditional on knowing the location of the sample member's household in at least one wave between ages 16-25. There are a small number of cases (~10%) where due to issues such as withdrawing from the survey or ineligibility, this is not known. The four categories are: "did not live with parents", "lived with parents less than 80% of the time, "lived with parents between 80 and 99% of the time" and the reference category "lived with parents 100% of the time". This measure was included to investigate whether living with parents had an effect on whether the sample member would respond in early adulthood. All other covariates were chosen based on existing literature and availability in the data (Gerry & Papadopoulos, 2015; Lugtig, 2014; Uhrig, 2008). Data management was undertaken and regression analyses were estimated in Stata 16 (StataCorp, 2019).

3.3 Results

3.3.1 Patterns of Youth Response

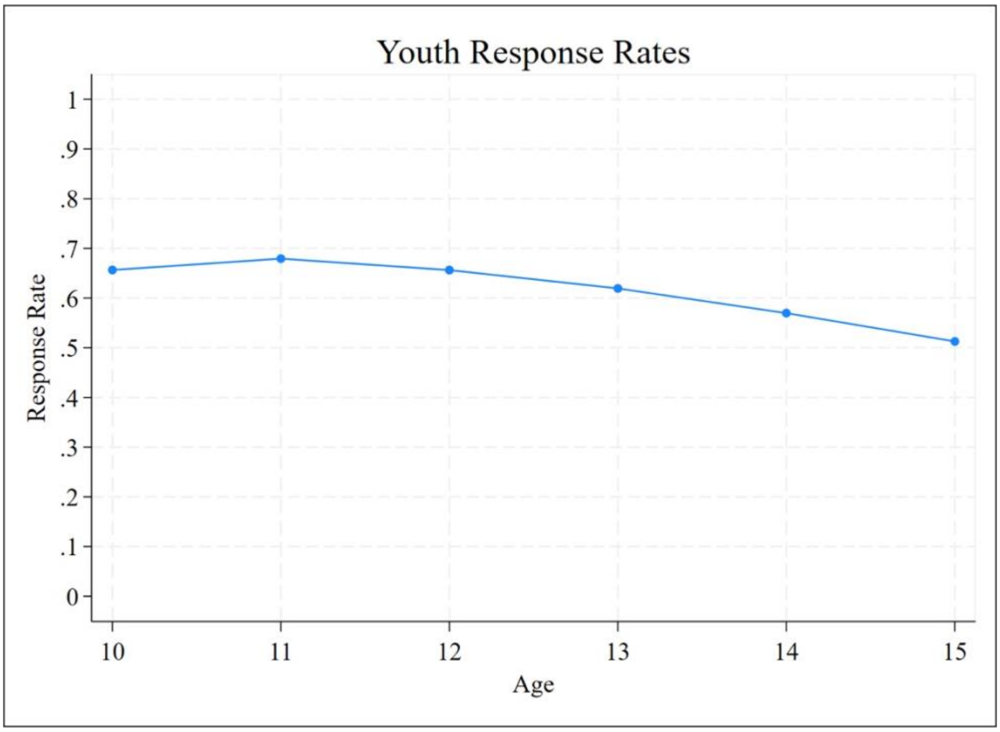


Figure 3.1: Youth response rates by age

Figure 3.1 depicts the youth response rates by age, computed by the number of respondents who completed a full youth interview at age *X* divided by the number of respondents enumerated in the survey at age *X*, where *X* is the specified age on the x-axis. At age 10, the response rate is 0.66 and this increases to 0.68 at age 11. From age 12 to 15, the response rate decreases from 0.66 to 0.51. This suggests that response to youth interviews decreases as the respondents age. However, as stated in the Introduction section, response behaviour is not necessarily linear so methods such as latent class analysis can provide more context.

In this analysis, the RMLCA included the six observed binary variables, which showed whether the sample member had completed a youth interview at each age between 10 and 15.

A set of nested models were estimated, where each model included an additional class. Table 3.2 shows the five best fitting models according to the model evaluation criteria. These five models contain 3 to 7 classes. As the number of classes increases, the model deviance decreases, implying that the models with higher number of classes have better fits. Similarly, for models 1 to 3, the BIC decreases as the number of classes increases, indicating better fits. However, this is not the case for models 4 and 5. The entropy values highlight how well the classes can be separated and values above 0.8 indicate a high amount of separation and are preferred. None of the models have values above 0.8, but Model 1 has a value above 0.6, so there is a moderate amount of separation between classes. Finally, the bootstrapped likelihood ratio test (BLRT) shows whether the nested model is a better fit than the previous one. Table 3.2 shows that each additional class improves the fit of the model.

Table 3.2: Model fit information and statistics for the five best fitting models

Model	Number of Classes	Deviance	*df*	BIC (LL)	Entropy	Class Size (% of sample) Min.	Max.	BLRT
1	3	58,289	464	58,477	0.609	18%	61%	0.000
2	**4**	**57,983**	**457**	**58,237**	**0.514**	**15%**	**49%**	**0.000**
3	5	57,903	450	58,223	0.503	7%	49%	0.000
4	6	57,879	443	58,264	0.450	6%	37%	0.000
5	7	57,858	436	58,309	0.515	4%	51%	0.000

Note: BIC = Bayesian Information Criterion; BLRT = Bootstrapped Likelihood Ratio Test.
N=12,171
Deviance = −2 × Log Likelihood.
The lowest value of the BIC indicates a better fitting model (*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*). The model shown highlighted in bold typeface was selected as the final model.

Table 3.2 also shows that conflicting conclusions about the preferred model can be drawn depending on the model fit statistic: Model 1 (entropy), Model 3 (BIC), Model 5 (deviance and BLRT). Therefore, it is important to also understand the interpretability of each model in the context of the data, which can be done by examining the parameters that are used to depict the response patterns (see Figure 3.2). Figure 3.2 (showing Model 2) depicts 4 unique response patterns over a six-year period. Firstly, Class 1 contains those who are very likely to respond to the youth interviews, whereas Class 2 are the least likely to respond. Class 3 start off with high response probabilities that decrease as the respondent ages into the teenage years, and Class 4 is the opposite, starting off with low response probabilities that increase as the respondent ages. Model 2 was selected for more in-depth analyses based on this interpretability in combination with the model fit statistics shown in Table 3.2.

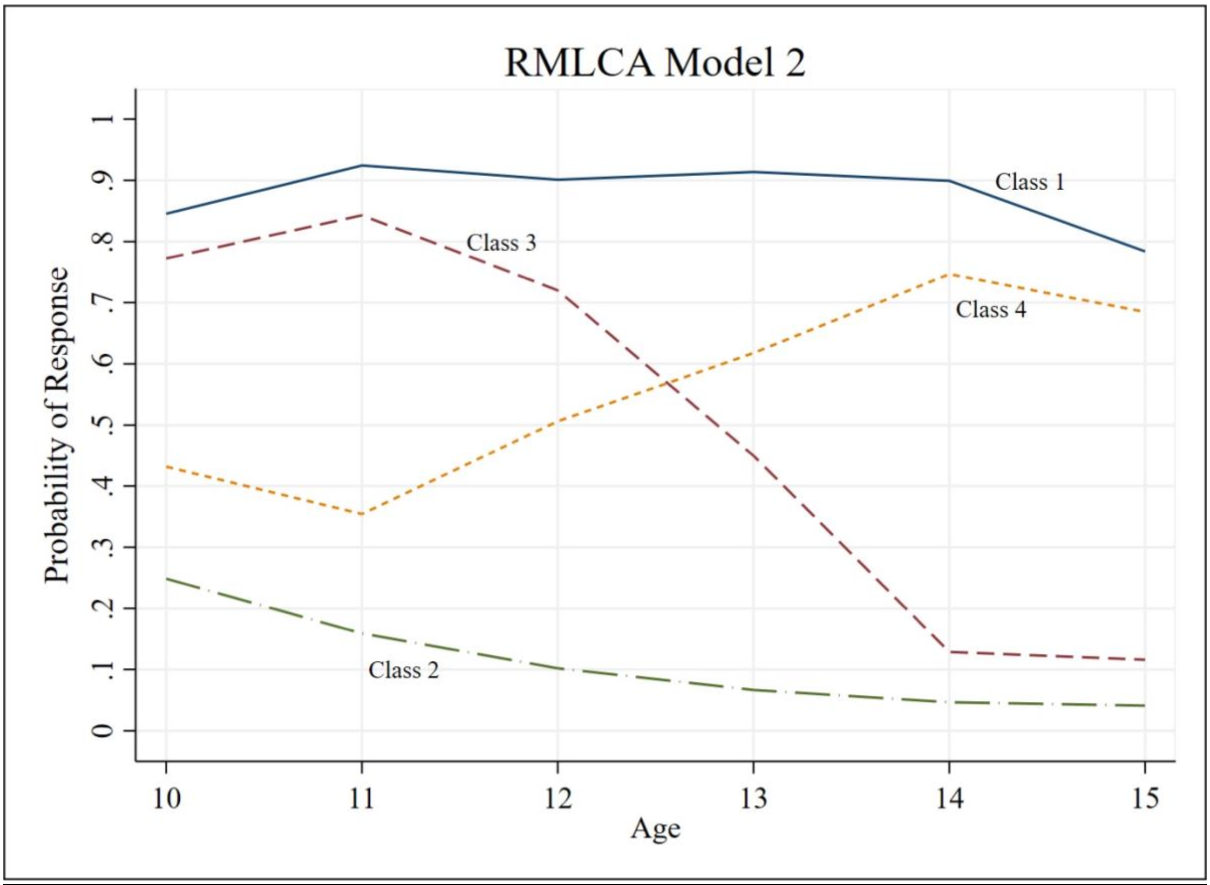


Figure 3.2: Response probabilities for Model 2 (4 classes)

Table 3.3 shows the summary statistics for Model 2. In the sample of 12,171 youth sample members, 49% are female and 30% are ethnic minorities. Class 1, the class with the highest response probabilities, comprises nearly half the sample. Class 2, the class with the lowest response probabilities, comprises a fifth of the sample. Classes 3 and 4 account for 16% and 15% of the sample, respectively. Class 3 begins with high response probabilities that decrease as age increases and Class 4 has the opposite pattern (low response probabilities, increasing as age increases). The four classes each have similar proportions for sex to the whole sample ranging from 45-50% of female respondents. However, only Classes 2 and 4 have similar proportions for ethnicity as the whole sample. Class 1 has a lower proportion (23%), and Class 3 has a higher (46%), implying that ethnic minority sample members have are less likely to respond in the youth waves, especially after age 12.

Table 3.3: Summary statistics for Model 2

Class	Class Size	% of Sample	% of Female Respondents	% of Ethnic Minority Respondents
1	5,908.3	49	50	23
2	2,493.5	20	47	33
3	1,928.9	16	45	46
4	1,840.2	15	49	34
Total	12,171.0	100	49	30

Note: The class sizes are in decimals as the BCH method was adopted and adjustments to account for sample members with unknown eligibility were made.

3.3.2 Early Adulthood Response

To investigate whether youth response behaviour can predict early adulthood response, a set of logistic regression models with different binary dependent variables were estimated. These dependent variables were: (1) whether or not the sample member completed their first full adult individual interview at age 16; (2) whether or not the sample member completed at least one full adult individual interview between ages 16-19; and (3) whether or not the sample member completed at least 80% of the eligible full adult interviews between ages 16-25 (see section 3.2.3 for discussion of why these variables were chosen for analyses). Two models were estimated given each dependent variable. The first considers the impact of RMLCA class membership and sociodemographic variables on whether a full interview was completed. The second is the same as the first but also considers the impact of additional household level variables including parental response. Average marginal effects are presented to aid in the interpretation and comparison of the findings and standard errors adjust for the complex sample design using the primary sampling unit and strata.

The average marginal effects are reported in Table 3.4. The results of Model 1, which included class membership and sociodemographic variables, suggest that those in Classes 2-4 were less likely to have completed a full interview at age 16 (the first adult interview), when compared with Class 1, the class with the highest youth response probabilities. Moreover, those who are female were more likely to have completed such an interview at 16 and those who are Indian were more likely to have done so than their White counterparts, whereas those who are Black, Mixed or Other were less likely to have done so.

When household-related covariates were added to this model (see Model 2), the coefficients in Model 1 for class membership and sex slightly decreased. Concerning ethnicity and when comparing to those who are White, the coefficients increased for those who are Indian, and Pakistani, and became not significant for the other groups, controlling for the household independent variables. In addition, those in households that had completed any web interviews (if eligible) were more likely to have completed a full interview at age 16 than those in households who had not. While the coefficients were all significant ($p < .05$) when compared to those in households that did not complete by web, they generally decreased as the proportion completed by web increased, which may indicate that having a mixed mode approach is more suitable. The coefficients for the different types of household composition and for household income were not significant. Concerning the impacts of parents, those with low or no parental response or no biological parents reported were less likely to have completed an interview at 16 than those with high parental response.

Models 3 and 4 are the models in which the dependent variable was whether or not the sample member completed at least one full individual interview between the ages of 16 and 19. Similar to Models 1 and 2, they suggest that those in Classes 2-4 are less likely to have completed at least one interview than those in Class 1, but the model coefficients in this model are somewhat higher, implying the association between class members and completing at least one full interview between ages 16-19 is slightly stronger. The coefficients for sex, ethnic minorities, household mode, and parental response are also similar but higher than in Models 1-2. The coefficients for different types of household composition and for household income remain nonsignificant.

Models 5 and 6 are the models in which the dependent variable was whether or not the sample member completed at least 80% of the eligible full interviews between ages 16-25. The coefficients for class membership in both models are much lower than in the previous four models, implying that the association between class membership and completing at most of the eligible interviews between 16-25 is weaker. However, the same relationships are maintained, with Class 1 being the most likely to have completed the interviews. Again, as with the previous four models, female sample members were more likely to have completed the interviews, although the coefficient was slightly larger. The coefficients for the different ethnic groups and household mode remain relatively similar.

Interestingly however, the coefficient household composition coefficients differ from the previous models, Models 2 and 4, implying that those with at least 1 adult (no couples) and children in the household are less likely than a couple with children in the household to respond. More specifically, those in a single parent household are even less likely to respond.

This suggests that while household composition is not important when recruiting youth sample members once they turn 16, it is in retaining them in the sample in early adulthood. Similarly, average household income, which was not significant in the previous analyses, is significant, suggesting that those with higher household incomes are more likely to respond in early adulthood. The coefficients for parental response are somewhat similar to the previous models, with those who have low or no parental response being significantly less likely to have completed at least 80% of the interviews in early adulthood.

Tables C2 and C3 (see Appendix C) model alternative measures of youth response on whether a full interview was completed in early adulthood. Table C2 models the percentage of youth interviews completed (i.e., number of youth interviews completed divided by the number of youth interviews eligible to complete) with the same sociodemographic and household variables. For all six models, those who have completed half or more of the eligible interviews and those who have completed all eligible interviewers are more likely to complete interviews in early adulthood than those who did not complete any youth interviews. Specifically, the more interviews completed, the more likely they are to complete interviews in early adulthood. Table C3 models the age of the sample member when they last completed a youth interview. For all six models, those who last completed an interview aged 13-15 were more likely to complete an early adulthood interview when compared to those that did not complete any youth interviews. Those who last completed an interview aged 10-12 were less likely to complete an early adulthood interview than those who did not complete any.

Table 3.4: Average marginal effects (AME) estimated from logistic regression models of class membership and other covariates on whether the sample member had completed (1) a full adult interview age 16, (2) at least 1 full adult interview age 16-19, (3) at least 80% of the full adult interviews between ages 16-25.

	Interview Age 16				1+ Interview Age 16-19				80%+ Interviews Age 16-25			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Class Membership (ref: Class 1)												
Class 2	-0.40***	(0.01)	-0.28***	(0.01)	-0.43***	(0.01)	-0.28***	(0.01)	-0.22***	(0.01)	-0.11***	(0.01)
Class 3	-0.50***	(0.01)	-0.35***	(0.01)	-0.54***	(0.01)	-0.35***	(0.01)	-0.27***	(0.01)	-0.14***	(0.01)
Class 4	-0.10***	(0.01)	-0.05***	(0.01)	-0.09***	(0.01)	-0.05***	(0.01)	-0.08***	(0.01)	-0.03***	(0.01)
Female	0.06***	(0.01)	0.05***	(0.01)	0.06***	(0.01)	0.05***	(0.01)	0.07***	(0.01)	0.06***	(0.01)
Ethnicity (ref: White)												
Black	-0.08***	(0.01)	-0.02	(0.02)	-0.06**	(0.02)	-0.00	(0.02)	-0.10***	(0.01)	-0.03*	(0.02)
Indian	0.05**	(0.02)	0.06**	(0.02)	0.06**	(0.02)	0.07**	(0.02)	0.05*	(0.02)	0.06**	(0.02)
Pakistani	0.02	(0.01)	0.06***	(0.02)	0.03	(0.02)	0.07***	(0.02)	0.01	(0.02)	0.05**	(0.02)
Bangladeshi	-0.01	(0.02)	0.04	(0.02)	0.03	(0.02)	0.07***	(0.02)	0.00	(0.02)	0.07***	(0.02)
Other Asian	-0.05	(0.03)	-0.01	(0.03)	-0.04	(0.03)	0.01	(0.03)	-0.07*	(0.03)	-0.03	(0.03)
Mixed	-0.06***	(0.02)	-0.03	(0.02)	-0.06**	(0.02)	-0.03	(0.02)	-0.03	(0.02)	-0.01	(0.02)
Other	-0.13**	(0.04)	-0.05	(0.04)	-0.13**	(0.04)	-0.05	(0.04)	-0.17***	(0.02)	-0.12***	(0.03)
Household Mode during 6 Youth Years (ref: None Completed by Web)												
Not Eligible to Complete by Web			0.23***	(0.01)			0.30***	(0.01)			0.10***	(0.01)
< Half Completed by Web			0.26***	(0.02)			0.33***	(0.02)			0.23***	(0.02)
Half or More Completed by Web			0.22***	(0.02)			0.31***	(0.02)			0.22***	(0.02)
All Completed by Web			0.20***	(0.02)			0.30***	(0.02)			0.25***	(0.02)
Average Household Composition (ref: Couple, children)												
1 adult, children			-0.01	(0.01)			-0.00	(0.01)			-0.05***	(0.01)
2+ adults (no couples), children			0.01	(0.01)			0.02	(0.01)			-0.03*	(0.01)
2+ adults (at least 1 couple), children			0.01	(0.01)			0.01	(0.01)			-0.01	(0.01)
Average Household Income			0.00	(0.00)			0.00	(0.00)			0.01*	(0.00)
Parents Completed Mostly Full Interviews (ref: Yes)												
No Bio Parents Reported			-0.32***	(0.05)			-0.33***	(0.05)			-0.26***	(0.05)
No			-0.30***	(0.01)			-0.31***	(0.01)			-0.31***	(0.01)

Note: The marginal effects are rounded to 2 decimal places and standard errors in parentheses.
* p < .05. ** p < .01. *** p < .001.
Model 1: N = 48,684. Model 2: N = 48,544.
Model 3: N = 48,684. Model 4: N = 48,544.
Model 5: N = 48,684. Model 6: N = 48,544.

3.3.3 Parental Influence

Table 3.5 includes a set of models estimated using a smaller dataset for which the relevant information on living arrangements was available (see section 3.2.3 for details) and average marginal effects are presented. They test whether living with at least one parent in early adulthood (ages 16-25) affects early adulthood response. The coefficients for class membership paint the same picture as the models described in the previous section (Models 1-6), with those in Class 1 with the highest response probabilities being more likely to respond in early adulthood. The coefficients for sex, ethnicity, household mode, household composition and household income are similar to the previous models.

Concerning the impact of living with parents, those who did not live at least one parent in early adulthood are less likely to have responded at age 16, between ages 16-19 and more than 80% of interviews between ages 16-25 than those who lived with at least one parent 100% of the time. However, although those who lived with their parents at least some of the time in early adulthood were also less likely to have responded to more than 80% of interviews between ages 16-25 than those who lived with at least one parent 100% of the time, those who lived with their parents at least some of the time in early adulthood are more likely to have responded at age 16 and between ages 16-19 than those who lived with at least one parent 100% of the time. To explore these latter, unexpected results further, similar models were run with those with low or no parental response excluded from the analysis dataset. The results of the analyses are reported in Table C4 in Appendix C. The coefficients in these models again show that those did not live with their parents during early adulthood were less likely to participate at age 16 and age 16-19 than those who lived with their parents 100% of the time (the dependent variable measuring those who responded to more than 80% of interviews between 16-25 was not included due to collinearity issues).

However, they also showed that those who lived with their parents less than 80% of the time during early adulthood were less likely to participate at age 16 and age 16-19 than those who lived with their parents 100% of the time, and that there were no significant differences between those who lived with their parents 80%-99% during early adulthood and the latter category. Hence, the aforementioned unexpected results are due to the inclusion of sample members with parents who have low survey response in the analysis dataset. Possibly, such individuals exhibited higher response rates because they did not live with their parents all the time, although given the lack of a similar effect in the analysis with responding to more than 80% of interviews aged 16-25 as the dependent variable it may be that this effect dissipates with time.

Table 3.5: Average marginal effects (AME) estimated from logistic regression models of class membership and other covariates on whether the sample member had completed (1) a full adult interview age 16, (2) at least 1 full adult interview age 16-19, (3) at least 80% of the full adult interviews between ages 16-25 (conditional on knowing household location age 16-25).

	Model 7		Model 8		Model 9	
	Interview Age 16		1+ Interview Age 16-19		80%+ Interviews Age 16-25	
	AME	SE	AME	SE	AME	SE
Class Membership (ref: Class 1)						
Class 2	-0.23***	(0.01)	-0.21***	(0.01)	-0.10***	(0.01)
Class 3	-0.30***	(0.01)	-0.29***	(0.01)	-0.13***	(0.01)
Class 4	-0.05***	(0.01)	-0.04***	(0.01)	-0.03***	(0.01)
Female	0.06***	(0.01)	0.05***	(0.01)	0.07***	(0.01)
Ethnicity (ref: White)						
Black	-0.02	(0.02)	0.00	(0.02)	-0.05**	(0.02)
Indian	0.06*	(0.02)	0.06**	(0.02)	0.05*	(0.02)
Pakistani	0.06***	(0.02)	0.08***	(0.02)	0.04*	(0.02)
Bangladeshi	0.04	(0.02)	0.08***	(0.02)	0.07**	(0.02)
Other Asian	-0.01	(0.04)	0.01	(0.03)	-0.03	(0.03)
Mixed	-0.03	(0.02)	-0.03	(0.02)	-0.02	(0.02)
Other	-0.06	(0.04)	-0.05	(0.04)	-0.13***	(0.03)
Household Mode during 6 Youth Years (ref: None Completed by Web)						
Not Eligible to Complete by Web	0.17***	(0.02)	0.23***	(0.02)	0.11***	(0.01)
< Half Completed by Web	0.20***	(0.02)	0.26***	(0.02)	0.20***	(0.02)
Half or More Completed by Web	0.16***	(0.02)	0.24***	(0.02)	0.19***	(0.02)
All Completed by Web	0.14***	(0.02)	0.23***	(0.02)	0.22***	(0.02)
Average Household Composition (ref: Couple, children)						
1 adult, children	-0.01	(0.01)	-0.01	(0.01)	-0.05***	(0.01)
2+ adults (no couples), children	-0.00	(0.02)	0.00	(0.01)	-0.03*	(0.01)
2+ adults (at least 1 couple), children	0.00	(0.01)	0.00	(0.01)	-0.02	(0.01)
Average Household Income	0.00	(0.00)	-0.00	(0.00)	0.01*	(0.00)
Parents Completed Mostly Full Interviews (ref: Yes)						
No Bio Parents Reported	0.17***	(0.03)	0.11***	(0.02)	0.19	(0.12)
No	-0.30***	(0.01)	-0.30***	(0.01)	-0.34***	(0.01)
Lived in Same Household as at Least 1 Parent in Early Adulthood (ref: 100%)						
Did not live with parents	-0.43***	(0.03)	-0.48***	(0.03)	-0.25***	(0.02)
Lived with parents <80%	0.05***	(0.01)	0.08***	(0.01)	-0.10***	(0.01)
Lived with parents 80%-99%	0.11***	(0.02)	0.17***	(0.02)	-0.05**	(0.01)

Note: The marginal effects are rounded to 2 decimal places and standard errors in parentheses.
* $p < .05$. ** $p < .01$. *** $p < .001$.
Model 1: N = 43,292.
Model 2: N = 43,292.
Model 3: N = 43,292.

3.4 Discussion

This paper investigated whether youth (aged 10-15) survey response behaviour can predict early adulthood (aged 16 to 25) response behaviour. Little is known about survey participation among these individuals (Omrani et al., 2019), except that they are more likely to attrite than older sample members (Lynn & Borkowska, 2018; Uhrig, 2008). Such attrition is an issue because it reduces dataset size, which decreases the precision of survey estimates, and differential attrition rates (compared to older individuals) may cause survey estimate nonresponse biases (Groves et al., 2009). It is also especially an issue in panel surveys, whose utility relies on repeated measurements of the same individuals (Lynn, 2009a). Moreover, the lack of knowledge about response behaviour is problematic because it prevents the development of strategies to reduce such attrition rates.

Research questions were addressed using data from UKHLS, an annual panel survey which asks sample members to complete a youth interview when aged 10-15, then an adult interview from age 16 onwards. As youths were repeatedly interviewed and so could exhibit different patterns of response behaviour (for example, completing all interviews or doing so intermittently), an RMLCA framework was used to quantify their behaviour. This method enables patterns of survey response to be identified and categorised into classes (see Collins and Lanza (2010) & section 3.2.2. for details). Class membership then was included as an independent variable in logistic regression models utilised to predict early adulthood response behaviour. Three binary dependent variables were used in models: (1) whether or not the sample member completed their first full adult individual interview at age 16, (2) whether or not the sample member completed at least one full adult individual interview aged 16-19, (3) whether or not the sample member completed at least 80% of the eligible full adult individual interviews between ages 16-25. In addition to class membership, other independent variables concerning youth personal and residing household (HH) characteristics were included. Also, parental response and whether or not they lived with one or more of their parents were included in the models; given their relationship, the latter may influence the response behaviour of individuals (Coyne 2010).

The RMLCA analysis identified four classes of youth response behaviour: 1) those with high response probabilities; 2) those with low response probabilities; 3) those with initially high response probabilities that decreased as they aged; and 4) those with initially low response probabilities that increased. The logistic regression analyses suggested that these patterns continued into adulthood, with in all models estimated Classes 2-4 less likely to complete interviews than Class 1 (though likelihoods for Class 4 where closer to those for Class 1 than those for the other classes). In addition, female sample members were more likely to complete interviews than their male counterparts, differences existed between ethnic groups (in particular, Indian sample members were more likely to complete interviews than their White counterparts, who were more likely to do so than Black sample members), and interviews were more likely to be completed if the HH completed web interviews than if it did not. HH income had a positive impact on the likelihood of completing 80%+ of interviews aged 16-25, but no impact when the other dependent variables were considered. Similarly, HH composition only had an impact on the former dependent variable: those living in a household including a couple and children were more likely to complete interviews than those living in other types of HHs. Moreover, sample members with parents who completed mostly full interviews were more likely to complete interviews than those who did not or who did not have parents reported. Those who lived in the same household with at least 1 parent between ages 16-25 were more likely to have responded.

These findings represent the first comprehensive investigation of the correlates of young adult survey response behaviour. This is important for several reasons. Firstly, and perhaps most notably, the findings demonstrate that youth response behaviour is a predictor of subsequent response behaviour as a young adult. UKHLS sample members identified as having high response probabilities during their youth years (or at least at their end) were also more likely to respond to the survey once they turned 16. This relationship has not previously been reported. This supports the “commitment” and “habit” theories of survey response, whereby individuals who respond to surveys tend to continue to do so (Lugtig, 2014). Interestingly, findings also suggested that those who completed less than half of their interviews were slightly less likely to interview in early adulthood, compared to those who did not complete any youth interviews. This could suggest an absence of “commitment”, where sample members have a negative experience with the survey and therefore do not complete that many youth interviews and then do not go on to complete the adult interviews. This should be of particular interest to survey designers, since it indicates who should be targeted by interventions seeking to improve dataset quality by increasing response rates among young adults: those with low and declining youth response probabilities. Concerning such interventions (e.g., incentives, motivating messages, extra contacts), the findings related to the other correlates of young adult response behaviour in terms of personal characteristics should also be accounted for in their design. For example, young adult male sample members are less likely to respond than their female counterparts and Black and White sample members are less likely to respond than Indian sample members may allow the further refinement of strategies, both in terms of who is targeted and in terms of the nature of the incentives offered (see Lynn (2017) for a review on targeted intervention strategies).

Moreover, the findings of this research are also important because they demonstrate the impact of parental influence on young adult response behaviour. Young adult sample members were more likely to respond to the UKHLS survey if their parents also did so, and also if they lived with their parents between the ages of 16-25. Again, to my knowledge, such relationships in panel surveys have not been reported before. The findings potentially support the aforementioned "commitment" and "habit" theories of survey response, except in this case, the commitment and habit are consequences of the response behaviour of parents in the HH. The findings also potentially support the "shock" theory where a changing event can cause sudden dropout. Those who did not live with their parents in early adulthood were less likely to participate in early adulthood despite high parental response. This also should be of particular interest to survey designers seeking to develop intervention strategies to increase response rates among these individuals. The knowledge that these relationships exist can be used to further refine the strategies discussed in the last paragraph: seek also to tailor them toward sample members whose parents did not respond to the survey, and sample members who do not live with their parents. Moreover, while it was beyond the scope of this paper, further research should be conducted on the ways in which common events or changes that occur in early adulthood, such as transitioning from school to work or university and leaving the parental home, affect early adulthood response and the intervention strategies that can be implemented to encourage response.

Additionally, given the findings concerning the impact of high youth response on young adult response, these findings suggest another, novel way by which response rates among young adults might be increased. This is to design intervention strategies (e.g., additional joint incentives) to improve response rates among adults with children who do not respond to the survey. As parents or guardians may act as gatekeepers to obtaining responses from their children (Coyne, 2010), survey designers could implement interventions strategies to improve response rates among adults with children who do not respond to the survey. If successful, such strategies should improve young adult response rates both though the impact of increased parental response on such rates and also through their impact on youth response rates.

Further research on this topic should now focus on designing the aforementioned intervention strategies to increase response rates among children. That said though, initially at least it is suggested that this research is confined to the UKHLS survey. This is because, in adults at least, the correlates of attrition may differ between countries and between surveys in the same countries, and even when commonalities exist, signs of the associations may vary (Behr et al., 2005; Luiten et al., 2020). Hence, it is recommended that designers working on other surveys begin their work on this topic by first seeking to replicate the analyses conducted in this paper to find out whether the patterns in terms of the correlates of young adult response observed in the UKHLS are also found in such surveys, or whether different patterns are observed.

Conclusion

This thesis investigated three aspects of survey participation in panel surveys, using different components of *Understanding* Society: The UK Household Longitudinal Study (UKHLS). Understanding who participates and who does not in surveys is important because the latter reduces respondent dataset size, which can decrease the precision of survey estimates. In addition, if nonresponse is non-random with respect to survey sample member characteristics, it may cause survey estimates to deviate from study population values (nonresponse biases). A further complexity in panel surveys, which repeatedly interview sample members at different time points, is that nonresponse can be restricted to a single survey wave, or members may drop out of the sample completely (i.e., panel attrition).

The research conducted generally used non-traditional approaches to studying the causes and correlates of survey participation and extends existing knowledge on the topic. The findings of this research have practical implications for nonresponse bias prevention techniques utilised during survey data collection and bias adjustment techniques utilised post-data collection to improve dataset quality as they can inform the adoption and/or modification of such techniques in the UKHLS and (potentially) other panel surveys. This chapter will first summarise the findings of the included research, then discuss its limitations, Next, the implications of the research are described, before finally recommendations for future research are presented.

Summary of Research Findings

Chapter 1

Chapter 1 investigated the characteristics of loyal survey sample members (those who respond to all survey waves) and how they differ from other sample members. A latent class analysis (LCA) framework was used, which, unlike other methods for studying survey participation, enabled consideration of those who participate intermittently (non-monotone attritors) as well as those who drop out completely (monotone attritors) and loyal sample members. Previously, only limited research has been undertaken on these different types of attritors from panel surveys (see Gerry and Papadopoulos (2015); Lugtig (2014)), so little is known about how (or whether) they differ. Additionally, the analysis implemented appropriate components for unknown eligibility. Concerning the latter, the possibility that uncontacted sample members assumed to have attrited have actually become ineligible due to moving out of scope, being incapacitated, or dying, is rarely considered in analyses of attrition even though it may lead to the misidentification of response patterns and attrition correlates.

The research in the chapter considered wave 1 participants from the predecessor to the UKHLS, the British Household Panel Survey (BHPS), whose remaining participants were included in the UKHLS sample at wave 2, meaning that they could potentially participate in 26 survey waves. Three questions were addressed: 1) what are the patterns of response for the BHPS sample?; 2) what are the characteristics of those that follow these patterns?; and 3) specifically, how do loyal sample members differ from those who follow other patterns?

LCA was used to identify the response patterns of the BHPS sample members, then based on these patterns they were categorised into groups. Measures to account for unknown eligibility were incorporated into the analyses using the life tables approach. National life tables provide population-level mortality rates separated by age and sex, which are then converted to survival rates. Those with an unknown eligibility status are weighted using these survival rates, which provide an estimate of their probability of survival in the waves where eligibility is not known. An LCA model with seven classes was chosen, given the model evaluation criteria and interpretability (i.e., whether classes have meaningful distinct patterns). The first class were loyal sample members, which constituting 34% of the 9,912 considered individuals. Three classes (50% of the sample) followed a monotone attrition pattern, attriting by wave 8, wave 16 and wave 22, respectively. Three classes (15% of the sample) followed a non-monotone attrition pattern, responding intermittently. These consisted of: 1) “stayers”, who had high response probabilities in the 18 BHPS waves, then declining probabilities after the transition to the UKHLS; 2) “gradually nudged”, who had declining response probabilities for the first half of BHPS, then probabilities that gradually increased and remained high; and 3) “abruptly nudged”, who had high response probabilities in the early waves of BHPS that had declined to the point of attrition by its end, then their probabilities sharply increased at the transition into the UKHLS before starting another gradual decline.

After individuals were classified into groups, multinomial regression was used to identify the characteristics of each group. In weighted analyses that accounted for unknown eligibility, loyal sample members were more likely to be white, older, and more highly educated. Those in classes that still remained in the sample (i.e., non-monotone attritors – “stayers”, “gradually nudged” and “abruptly nudged”) had more similar characteristics to the “loyal” class than the classes that exhibited monotonic attrition response pattern. Despite this, distinguishing between monotone and non-monotone attritors is still important, for example, it highlighted that ethnic minority respondents were more likely to be in the "gradually nudged" class.

The unweighted analyses that assumed that everyone in the sample was eligible to participate were also presented in Appendix A. In these, the response patterns identified, and class sizes changed slightly. Seven classes were identified, consisting of "loyal" sample members (34% of the 9,912 individuals), four classes of monotone attritors (52% of the sample), who attrited by wave 8, 14, 22 and 23 respectively, and two classes of non-monotone attritors (14% of the sample): "stayers" and "nudged". The "stayers" class was similar to its weighted counterpart. The response pattern of "nudged" class was more reminiscent to that of the "abruptly nudged" class in the weighted model as both patterns showed a sharp increase in response probabilities from BHPS wave 18 to UKHLS wave 2. The coefficients of the multinomial regression model used to identify the characteristics of the different classes were similar to those in the weighted analysis, although it is important to distinguish between their interpretations: weighted models measured the correlates of attrition, while the unweighted models measured the correlates of attrition and death.

Chapter 2

Chapter 2 considered the impact of the recent COVID-19 pandemic on survey dataset quality. The pandemic significantly affected how surveys were administered. Face to face (F2F) interviewing was suspended, so instead primarily web-based designs were used. Data collection was also often more frequent, to collect information on pandemic impacts (Blom et al., 2020; Brown et al., 2021; Burton et al., 2020; Gummer et al., 2020). Although the former mode shift had been occurring pre-pandemic, albeit at a slower pace and not to the same extent, such design changes were made with limited information on their effect on (and issues impacting on) survey dataset quality in terms of likely nonresponse biases.

An example of this occurred with the UKHLS. The main survey is an annual panel survey with (in the pre-pandemic era) a mixed mode design (including F2F). In response to the pandemic, the UKHLS COVID-19 Study was also fielded, in which main survey participants were invited to complete (mostly) bi-monthly web questionnaires. The research in this chapter investigated the extent to which information on survey dataset quality in terms of likely nonresponse biases in the pre-pandemic main survey was predictive of similar in the COVID-19 Study. The research questions addressed were: 1) how does the quality in terms of likely nonresponse biases of the pre-pandemic UKHLS main survey datasets, in which F2F interviewing was utilised, compare to that of the primarily web-based and more frequently collected UKHLS COVID-19 Study datasets?; and 2) how do dataset quality issues (in terms of response propensity variation associated with auxiliary covariates and their categories that may cause nonresponse biases) compare in the two surveys?

Representativeness indicators (Schouten et al., 2009; Schouten et al., 2016; Schouten et al., 2011) were used to evaluate survey dataset quality. These quantify variation in sample member response propensities estimated given an auxiliary covariate set, with low levels implying low likely biases, and the variant used, the Coefficient of Variation of response propensities (CV), quantifying the maximal absolute standardised bias of survey estimates. Partial decompositions also exist that quantify propensity variation associated with auxiliary covariates and their categories: the likely cause of biases, and potentially addressable by use of bias prevention and adjustment techniques. Longitudinal survey datasets, including those who also responded in all previous waves, were evaluated along with cross-sectional datasets.

So that auxiliary covariates were available for non-respondents, analysis samples consisted of wave 1 respondents to each survey. These were weighted so that they mapped sample members to the survey eligible samples and, putatively, the UK population at the relevant time points.

Findings suggested that information on main survey dataset quality was of limited value for predicting similar in the COVID-19 Study. Most likely due to the aforementioned design differences and also changes in participants lives due to the pandemic, overall dataset quality patterns across waves differed in the two surveys. In addition, propensity variation associated with auxiliary covariates and their categories varied. Patterns across waves and the ranking of covariate impacts in terms of associated propensity variation differed, and as in a number of instances did whether covariate categories were over- or under-represented (respectively more or less common than in the survey sample) in datasets.

Chapter 3

Chapter 3 examined the response behaviour of youth respondents to assess whether it could predict early adulthood response. The latter individuals are more likely to attrite from surveys than their older counterparts (Lipps, 2009; Lynn & Borkowska, 2018; Uhrig, 2008; Watson & Wooden, 2009), potentially causing nonresponse biases, but otherwise little is known about their response behaviour or its correlates. In particular, while assumed, there is limited knowledge on the role of parents in influencing the response behaviour of such individuals (Coyne, 2010; Ireland & Holloway, 1996). In the research, the UKHLS datasets were used. The UKHLS enumerates sample members from birth, they are eligible to complete youth interviews from ages 10-15 and adult interviews from age 16 onwards. Existing youth sample members (i.e., in the study sample before age 16) that are eligible to participate are known as "rising 16s". Given this study design, youth response can be theoretically thought of as both recruitment (the first adult interview at age 16) and retention (continuing to remain in the study sample). Survey designers also have to consider the parents or guardians of these sample members and whether they will influence them to participate or not (Scott, 1997, 2008). The research questions were: 1) can survey response behaviour in youth predict subsequent survey response behaviour as a young adult? 2) how important is parental influence behaviour in predicting youths' response behaviour as a young adult?

To address the research questions, first latent class analysis (LCA) was used to identify and categorise patterns of response behaviour of youth sample members between the ages of 10-15. Then, logistic regression modelling was utilised to investigate the correlates of young adult (aged 16-25) response behaviour, with the classes of youth response behaviour identified by the LCA analysis, sample member personal and residing HH characteristics, and information of parental response to the survey included as independent variables. An LCA model with four classes of youth response behaviour was chosen. Youth response patterns were categorised into 1) those with high response probabilities; 2) those with low response probabilities; 3) those with initially high response probabilities that decreased as they as aged; 4) those with initially low response probabilities that increased as they aged. The logistic regression models suggested that those in Class 1 were the most likely to complete an adult interview. Those in Class 4 were more likely to complete adult interviews than those in Classes 2 and 3, suggesting that response at ages 13-15 is more important than at ages 10-12. Additionally, the models showed that sample members were more likely to complete adult interviews when their parents exhibited high levels of response to the survey, and when they lived with their parents aged 16-25.

Limitations of Research

The research reported in this thesis has two main limitations, both of which are common in work on survey design. First, many of its findings are concerned with identifying the correlates of survey participation. As noted in the Introduction to this chapter, a major reason for undertaking such work is so that it can inform the use of techniques to reduce survey estimate nonresponse biases. One issue with this, however, is that as relevant population values were not available actual survey estimate nonresponse biases could not be quantified. As noted above, this is generally the case in research of this type (see Hand et al. (2018) for discussion). That said however, even without this information ensuring that datasets closely reflect the survey eligible sample/the study population is considered to improve dataset quality, since work has shown that estimates from such datasets are less likely to exhibit biases (Moore et al., forthcoming; Schouten et al., 2016)).

The second limitation concerns the generalisability of findings. The correlates of survey participation have been shown to differ between countries and between surveys, and even when commonalities exist, the signs of the associations can vary (Behr et al., 2005; Luiten et al., 2020). Moreover, such associations may differ over time even within a survey, due to survey mode shifts, technological advances, and societal changes (Olson & Witt, 2011). Hence, in terms of informing on similar correlates in other surveys, the findings in this thesis are perhaps best described as contributing to a non-exhaustive list of potential correlates that even if they do impact on attrition rates, may do so in a different manner to in the UKHLS surveys. Similar can be said with regard to the correlates of attrition in the UKHLS surveys in future, with perhaps the take home message being that, although onerous, such research should be revisited at regular intervals to ensure that its findings are still relevant.

Implications of Research and Contribution to Literature

Chapter 1

The findings of the research in Chapter 1 suggest that the characteristics of attritors from the UKHLS survey (and its predecessor, the BHPS) differ from those of loyal sample members who responded to all survey waves, although there were some similarities between the latter and non-monotone attritors (those who responded intermittently rather than dropping out completely, with the latter termed monotone attritors). Now that the characteristics of these (different types of) attritors have been identified, it may be possible to target them with intervention strategies designed to encourage them to continue to participate or to participate more consistently in the survey. If such interventions are successful, they will increase in particular longitudinal dataset size (the main focus of panel surveys), which in turn should increase dataset quality by increasing the precision of survey estimates. In addition, this increased participation should result in reduced differences between the survey sample (and therefore the study populations) and datasets in terms of the characteristics of individuals. Notwithstanding the limitations of this research outlined previously, this is likely to also increase dataset quality by reducing survey estimate nonresponse biases.

This research makes several contributions to the survey design literature. To begin with, it expands understanding of the correlates of attrition by considering the response process as a whole, rather than focusing on the notion that the first instance of nonresponse is solely important. This was facilitated by the use of a latent class analysis framework to investigate the research questions, an approach that has previously rarely been used to in studies of survey attrition (see Lugtig (2014); Gerry and Papadopoulos (2015) for exceptions). This approach led to the identification of different types of response behaviour, implying that a more nuanced approach than is currently utilised is required to maximise the benefits of intervention strategies designed to reduce attrition. As such, the research findings should be of interest to designers seeking to maximise dataset quality in their own surveys.

In addition, the research reported here contributes to the literature by considering unknown sample member eligibility. This is an important topic in long-running panel surveys that has received limited attention (for exceptions, see Sadig (2014, 2015); Watson (2016)). In such surveys, a substantial proportion of the original sample can be expected to become ineligible (i.e., to have moved out of the scope of the survey, to have become mentally or physically incapacitated, or to have died) during the survey lifecycle (Burton et al., 2004). Not knowing the eligibility status of attrited sample members can bias inferences made about the study population, as ineligible cases (e.g., those who have moved out of the scope of the survey or have died) should be excluded. Equally, being able to make inferences about the eligibility status of such individuals can aid in deciding whether or not to allocate resources to help to locate, contact and encourage them to participate in the survey. The research in this chapter should highlight this issue and motivate further investigation of it by survey designers, while the methods used provide a way for them to account for its effects in their own research on panel attrition.

Chapter 2

The findings of the research in Chapter 2 suggest that the UKHLS main survey was of limited value for informing on UKHLS COVID-19 Study dataset quality in terms of likely nonresponse biases and issues impacting on it. The findings concerning response propensity variation associated with auxiliary covariates and their categories are especially of note. They imply that if bias prevention or adjustment techniques developed in light of quality issues in the main survey had been utilised in the COVID-19 Study, their outcomes may have differed (in actuality, custom techniques were used in the Study – see section 2.5 for discussion). As mentioned previously, the differences found between the two surveys are likely to be due to the changes in survey design and participants lives caused by the COVID-19 pandemic. Overall, they suggest that targeted research, which was not possible given the speed with which the pandemic affected society, would have been needed to make accurate predictions concerning COVID-19 Study dataset quality.

This research makes several contributions to the survey design literature. To begin with, it represents the first comparison of (issues impacting on) dataset quality in the UKHLS main survey with similar in the UKHLS COVID-19 Study. This comparison is important even though the COVID-19 pandemic and the COVID-19 Study have ended. Other pandemics may occur in future and lead to similar new surveys. In addition, the shift to web mode in the COVID-19 Study was already occurring in the main survey, but at a slower pace and not to the same extent (Institute for Social and Economic Research, 2022). Web mode reaches a wider range of sample members and has lower time and financial costs than F2F mode (Bethlehem, 2008; Couper, 2000; Jäckle et al., 2015; Knoef & de Vos, 2009; Scherpenzeel, 2011). Hence, one day it may completely replace F2F mode in the main survey as well (though currently there are no plans to do so). Should either of these events occur, the findings here suggest that targeted research will be needed to predict effects on dataset quality in the UKHLS surveys.

In addition, the research reported here contributes to the literature more generally. Both in the UK and elsewhere, other new surveys were fielded during COVID-19 pandemic (e.g., Blom et al. (2020); Brown et al. (2021); Burton et al. (2020); Gummer et al. (2020)). These were also often derived from existing surveys and involved similar design changes and were fielded with limited information on how dataset quality would be affected. Moreover, the increased use of web mode outside of the pandemic context is universal (Bianchi et al., 2017; Burton & Jäckle, 2020; Cornesse & Bosnjak, 2018; Couper et al., 2007; Institute for Social and Economic Research, 2022; Nicolaas et al., 2014). Consequently, that in such situations information from existing surveys is likely to be of limited use for predicting dataset quality, and that instead targeted research is needed, should be of broad interest to survey designers.

Chapter 3

The findings of the research in Chapter 3 suggest that in the UKHLS youth (aged 10-15) response behaviour is a predictor of young adult (aged 16-25) response behaviour, with those less likely to respond as youths also less likely to respond as young adults. This implies that targeted intervention strategies focused on youths with low response probabilities may be successful in increasing their participation in the survey as young adults. Findings also suggest that parents influence young adult response behaviour, with higher young adult response among those whose parents also responded well to survey, and among those who live with their parents as young adults. This again suggests routes by which young adult survey participation may be increased: by utilising intervention strategies focused on parents with children with low response rates to the survey and on young adults who do not live with their parents. If successful, these strategies will increase survey dataset size, increasing the precision of survey estimates, and also, by ensuring the datasets more closely reflect the study population, reduce nonresponse biases.

This research makes several contributions to the survey design literature. To begin with, to my knowledge, it represents the first comprehensive investigation of young adult response behaviour. As such, its findings should be of interest to survey designers because they expand understanding of survey participation and attrition. In this context, the research should also be of interest to designers because it describes previously rarely used methods (LCA) that they can use to investigate similar questions in their own surveys. In addition, the research contributes to the literature with regard to the understanding of the mechanisms underlying survey participation. This is because its findings support the “commitment” and “habit” theories (Lugtig, 2014), whereby individuals who respond to surveys tend to continue to do so, is an important part of survey participation. Specifically, the findings suggest that commitment (and potentially habits) formed as youths are important for young adult response, and that they may have a household component, with those in HHs where other members (i.e., parents/guardians) respond to the survey being more likely to respond. Despite this, this age group are in a transitional period of the life course, (i.e., moving from the parental home, finishing education and joining the work force) so response habits may be broken during this period. These findings should be of interest to researchers focused on the psychological aspects of survey participation.

Recommendations for Future Research

Concerning Chapter 1, future related research in the UKHLS should focus on attempting to design effective intervention strategies to increase participation by the different groups of attritors. For example, groups that have not responded at every wave but still have high response probabilities, or groups that overall have declining response probabilities but show a pattern with gradual or sudden increases (as shown with the “nudged” classes). It may be that different types of intervention (e.g., extra reminder mailings, increased respondent incentives) lead to more success in increasing participation rates with these classes, especially if ways can be found to further tailor interventions given the (admittedly minor) differences in characteristics between groups.

Moreover, regarding related future research on surveys other than the UKHLS, it is suggested that designers first replicate the analyses in Chapter 1 in these surveys before attempting to design intervention strategies based on them. This is because, as noted in the "Limitations of research" section, it has been shown that the correlates of attrition often differ between different surveys within and between countries, and even when commonalities exist the signs of relationships may differ (Behr et al., 2005; Luiten et al., 2020). Hence, patterns of response behaviour/attrition and their correlates may differ in these surveys.

Concerning Chapter 2, future related research in the UKHLS should focus on designing effective intervention strategies to increase participation rates in under-represented sub-groups identified in the analyses of the main survey datasets. Some of this research is already being undertaken. It could also focus on the issues impacting on survey dataset quality of shifting to an entirely web-based design in the main survey, which, as noted in the "Implications of research and contribution to literature" section, could occur at some point in the future. This would be difficult to undertake in the main survey itself, but could possibly be considered in the UKHLS Innovation Panel (Institute for Social and Economic Research, 2022), a subsidiary survey specifically undertaken to test new development, before deciding whether or not to implement them in the main survey.

Moreover, survey designers of other surveys could use similar evaluation methods to see whether dataset quality and issues impacting on it also differed between their COVID-19 pandemic era surveys and their pre-pandemic parent surveys (i.e., whether the latter surveys were also of limited value for informing on such questions in the former). More importantly though, would be to investigate the effect on (and issues impacting on) survey dataset quality of shifting to entirely web-based design in these surveys (which could also occur in future in these surveys), although again there could be difficulties with undertaking this research.

Concerning Chapter 3, future related research in the UKHLS should focus on using the research findings to design effective intervention strategies to increase survey participation by young adults. For example, youths with (different patterns of) low response probabilities could be targeted, along with young adults not living with their parents and, given that youth response probabilities are correlated with parent probabilities, adults with children who have low response probabilities themselves. It may be found that different types of intervention strategy work better with different groups (for example, joint incentives for the whole family when parent response probabilities are also low), a possibility that should be evaluated using experimental methods. Concerning related future research in other surveys, as with similar questions regarding the work in Chapter 1 (see previously), it is suggested that first designers first attempt to replicate the work in this chapter before designing and testing intervention strategies. More specifically, given that it is unlikely that there will be a new large-scale household panel study (similar to UKHLS) in the foreseeable future, the general findings can also be applied to ongoing or new cohort studies. Cohort studies such as Next Steps (a cohort study focusing on young people's transitions to adulthood) face similar attrition issues (Calderwood et al., 2021). While response patterns and correlates may differ from those observed in UKHLS (e.g., due to the differences in survey design and the sample structure), a latent class approach would help in identifying the sub-groups of sample members that may be less inclined to respond as a prerequisite to testing targeted intervention strategies.

References

Baker, R., Blumber, S. J., Brick, J. M., Couper, M. P., Courtright, M., Dennis, J. M., Dillman, D., Frankel, M. R., Garland, P., Groves, R. M., Kennedy, C., Krosnick, J., Lavrakas, P. J., Lee, S., Link, M., Piekarski, L., Rao, K., Thomas, R. K., & Zahs, D. (2010). AAPOR REPORT ON ONLINE PANELS. *Public Opinion Quarterly*, *74*(4), 711-781.

Bakk, Z., Tekle, F. B., & Vermunt, J. K. (2013). Estimating the Association between Latent Class Membership and External Variables Using Bias-adjusted Three-step Approaches. *Sociological Methodology*, *43*(1), 272-311. https://doi.org/10.1177/0081175012470644

Behr, A., Bellgardt, E., & Rendtel, U. (2005). Extent and Determinants of Panel Attrition in the European Community Household Panel. *European Sociological Review*, *21*(5), 489-512. https://doi.org/10.1093/esr/jci037

Benzeval, M., Bollinger, C. R., Burton, J., Crossley, T. F., & Lynn, P. (2020). The Representativeness of Understanding Society [Working Paper]. *Understanding Society Working Paper Series, 2020-08*.

Bethlehem, J. (2008). Representativity of Web Surveys: An illusion? In I. Stoop & M. Wittenberg (Eds.), *Access Panels and Online Research, Panacea or Pitfall? Proceedings of the DANS symposium*. (pp. 19-44). Aksant.

Bianchi, A., & Biffignandi, S. (2017). Representativeness in panel surveys. *Mathematical Population Studies*, *24*(2), 126-143. https://doi.org/10.1080/08898480.2016.1271650

Bianchi, A., Biffignandi, S., & Lynn, P. (2017). Web-Face-to-Face Mixed-Mode Design in a Longitudinal Survey: Effects on Participation Rates, Sample Composition, and Costs. *Journal of Official Statistics*, *33*(2), 385-408.

Blom, A. G., Cornesse, C., Friedel, S., Krieger, U., Fikel, M., Rettig, T., Wenz, A., Juhl, S., Lehrer, R., Möhring, K., Naumann, E., & Reifenscheid, M. (2020). High-Frequency and High-Quality Survey Data Collection: The Mannheim Corona Study. *Survey Research Methods*, *14*(2), 171-178. https://doi.org/10.18148/srm/2020.v14i2.7735

Borgers, N., de Leeuw, E., & Hox, J. (2000). Children as Respondents in Survey Research: Cognitive Development and Response Quality. *Bulletin de Méthodologie Sociologique*, *66*, 60-75.

Borkowska, M. (2019). Improving Population and Sub-Group Coverage: Who is missing and what can be done about it? *Understanding Society Working Paper Series, 2019-15*.

Branden, L., Gritz, R. M., & Pergamit, M. R. (1995). *The Effect of Interview Length on Attrition in the National Longitudinal Survey of Youth* (National Longitudinal Surveys Discussion Paper, Issue NLS 95-28).

Brown, M., Goodman, A., Peters, A., Ploubidis, G. B., Sanchez, A., Silverwood, R., & Smith, K. (2021). *COVID-19 Survey in Five National Longitudinal Studies: Waves 1,* *2 and 3 User Guide*. UCL Centre for Longitudinal Studies and MRC Unit for Lifelong Health and Ageing.

Burton, J., & Jäckle, A. (2020). Mode Effects [Working Paper]. *Understanding Society Working Paper Series, 2020-05*.

Burton, J., Laurie, H., & Lynn, P. (2004). The Long-Term Effectiveness of Refusal Conversion Procedures on Longitudinal Surveys [Working Paper]. *ISER Working Paper Series, 2004-11*.

Burton, J., Lynn, P., & Benzeval, M. (2020). How *Understanding Society*: The UK Household Longitudinal Study Adapted to the COVID-19 Pandemic. *Survey Research Methods, 14*(2), 235-239. https://doi.org/10.18148/srm/2020.v14i2.7746

Calderwood, L., Peycheva, D., Henderson, M., Silverwood, R., Mostafa, T., & Rihal, S. (2021). *Next Steps: Sweep 8 - Age 25 User Guide*.

Calderwood, L., Smith, K., Gilbert, E., Rainsberry, M., Knibbs, S., & Burston, K. (2015). Securing Participation and Getting Accurate Answers from Teenage Children in Surveys: Lessons from the UK Millennium Cohort Study. *Social Research Practice*(1), 27-32.

Canberra Group. (2011). *Handbook on Household Income Statistics* (2nd ed.). United Nations.

Carpenter, J. R., & Kenward, M. G. (2012). *Multiple Imputation and its Application*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119942283.ch2

Collins, L. M., & Flaherty, B. P. (2009). Latent Class Models for Longitudinal Data. In J. A. Hagenaars & A. L. McCutcheon (Eds.), *Applied Latent Class Analysis* (pp. 287-303). Cambridge University Press. https://doi.org/10.1017/CBO9780511499531

Collins, L. M., & Lanza, S. T. (2010). *Latent Class and Latent Transition Analysis With Applications in the Social, Behavioral, and Health Sciences*. John Wiley & Sons, Inc.

Cornesse, C., & Bosnjak, M. (2018). Is There an Association between Survey Characteristics and Representativeness? A Meta-Analysis. *Survey Research Methods, 12*(1), 1-13.

Couper, M. P. (2000). Review: Web Surveys: A Review of Issues and Approaches. *The Public Opinion Quarterly, 64*(4), 464-494. https://www.jstor.org/stable/3078739

Couper, M. P., Kapteyn, A., Schonlau, M., & Winter, J. (2007). Noncoverage and Nonresponse in an Internet Survey. *Social Science Research, 36*(1), 131-148. https://doi.org/10.1016/j.ssresearch.2005.10.002

Coyne, I. (2010). Research with Children and Young People: The issue of parental (proxy) consent. *Children & Society, 24*(3), 227-237. https://doi.org/10.1111/j.1099-0860.2009.00216.x

Daikeler, J., Bošnjak, M., & Lozar Manfreda, K. (2020). Web Versus Other Survey Modes: An Updated and Extended Meta-Analysis Comparing Response Rates. *Journal of Survey Statistics and Methodology, 8*(3), 513-539. https://doi.org/10.1093/jssam/smz008

Davis-Kean, P., Chambers, R. L., Davidson, L. L., Kleinert, C., Ren, Q., & Tang, S. (2018). *Longitudinal Studies Strategic Review: 2017 Report to the Economic and Social Research Council*.

de Heij, V., Schouten, B., & Shlomo, N. (2015). *RISQ Manual 2.1: Tools in SAS and R for the computation of R-indicators, partial R-indicators and partial coefficients of variation*. Representativity Indicators for Survey Quality. https://hummedia.manchester.ac.uk/institutes/cmist/risq/RISQ-manual-v21.pdf

de Leeuw, E., & de Heer, W. (2002). Trends in Household Survey Nonresponse: A Longitudinal and International Comparison. In R. Groves, D. Dillman, J. L. Eltinge, & R. J. Little (Eds.), *Survey Nonresponse* (pp. 41-54). Wiley.

Eisner, N. L., Murray, A. L., Eisner, M., & Ribeaud, D. (2019). A Practical Guide to the Analysis of Non-Response and Attrition in Longitudinal Research using a Real Data Example. *International Journal of Behavioral Development, 43*(1), 24-34. https://doi.org/10.1177/0165025418797004

Fisher, P., Fumagalli, L., Buck, N., & Avram, S. (2019). Understanding Society and its Income Data. *Understanding Society Working Paper Series, 2019-08.*

Fitzgerald, J., Gottschalk, P., & Moffitt, R. (1998). An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics. *The Journal of Human Resources, 33*(2), 251-299. https://doi.org/10.2307/146433

Frankel, L. L., & Hillygus, D. S. (2014). Looking Beyond Demographics: Panel Attrition in the ANES and GSS. *Political Analysis, 22*(3), 336-353. http://www.jstor.org/stable/24573074

Fuchs, M. (2005). Children and Adolescents as Respondents. Experiments on Question Order, Response Order, Scale Effects and the Effect of Numeric Values Associated with Response Options. *Journal of Official Statistics, 21*(4), 701.

Fumagalli, L., Knies, G., & Buck, N. (2017). *Understanding Society The UK Household Longitudinal Study: Harmonised British Household Panel Survey (BHPS) User Guide*. University of Essex.

Gerry, C. J., & Papadopoulos, G. (2015). Sample Attrition in the RLMS, 2001–10. *Economics of Transition and Institutional Change, 23*(2), 425-468.

Groves, R. M. (2006). Nonresponse Rates and Nonresponse Bias in Household Surveys. *Public Opinion Quarterly, 70*(5), 646-675. https://doi.org/10.1093/poq/nfl033

Groves, R. M., Cialdini, R. B., & Couper, M. P. (1992). Understanding The Decision to Participate in a Survey. *Public Opinion Quarterly*, *56*(4), 475-495. www.jstor.org/stable/2749203

Groves, R. M., Fowler, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2009). *Survey Methodology* (2nd ed.). Wiley.

Groves, R. M., & Peytcheva, E. (2008). The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis. *Public Opinion Quarterly*, *72*(2), 167-189. https://doi.org/10.1093/poq/nfn011

Gummer, T., Schmiedeberg, C., Bujard, M., Christmann, P., Hank, K., Kunz, T., Lück, D., & Neyer, F. J. (2020). The Impact of COVID-19 on Fieldwork Efforts and Planning in Pairfam and FReDA-GGS. *Survey Research Methods*, *14*(2), 223-227. https://doi.org/10.18148/srm/2020.v14i2.7740

Hand, D. J., Babb, P., Zhang, L.-C., Allin, P., Wallgren, A., Wallgren, B., Blunt, G., Garrett, A., Murtagh, F., Smith, P. W. F., Elliott, D., Nason, G., Powell, B., Moore, J. C., Durrant, G. B., Smith, P. A., Chambers, R. L., Herzberg, A. M., Pilling, M., Appleby, W., Barnett, A., Bhansali, R., Bharadwaj, N., Dong, Y., van den Brakel, J. A., Budd, L., Doidge, J., Gilbert, R., Francis, B., Frisoli, K., Nugent, R., Perez, F. J. G., Lara, L., Porcu, E., Henry, S., Hunt, I., Ieva, F., Gasperoni, F., Jansson, I., Kumar, K., Longford, N., Manninen, A., Mateu, J., McNicholas, P. D., McNicholas, S. M., Tait, P. A., Mehew, J., Oberski, D. L., Ruiz, M., Yohai, V. J., Zamar, R., Stehlík, M., Stehlíková, S., Soza, L. N., Towers, J., & Wijayatunga, P. (2018). Statistical Challenges of Administrative and Transaction Data. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *181*(3), 555-605.

Hawkes, D., & Plewis, I. (2006). Modelling Non-Response in the National Child Development Study. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *169*(3), 479-491. https://doi.org/10.1111/j.1467-985X.2006.00401.x

Heron, J., Croudace, T. J., Barker, E. D., & Tilling, K. (2015). A Comparison of Approaches for Assessing Covariate Effects in Latent Class Analysis. *Longitudinal and Life Course Studies*, *6*(4), 420-434.

Institute for Social and Economic Research. (2021a). *Understanding Society COVID-19 Study: Participant Communication Materials*. University of Essex. https://www.understandingsociety.ac.uk/documentation/covid-19/fieldwork-documents/

Institute for Social and Economic Research. (2021b). *Understanding Society COVID-19 User Guide*. University of Essex. https://www.understandingsociety.ac.uk/sites/default/files/downloads/documentation/covid-19/user-guides/covid-19-user-guide.pdf

Institute for Social and Economic Research. (2022). *Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009, User Guide*. University of Essex.

Ireland, L., & Holloway, I. (1996). Qualitative Health Research with Children. *Children & Society*, *10*(2), 155-164. https://doi.org/10.1111/j.1099-0860.1996.tb00465.x

Jäckle, A., Lynn, P., & Burton, J. (2015). Going Online with a Face-to-Face Household Panel: Effects of a Mixed Mode Design on Item and Unit Non-Response. *Survey Research Methods*, *9*(1). https://doi.org/10.18148/srm/2015.v9i1.5475

Kenward, M. G., & Carpenter, J. R. (2007). Multiple Imputation: Current perspectives. *Statistical Methods in Medical Research*, *16*(3), 199-218. https://doi.org/10.1177/0962280206075304

Kim, S.-Y. (2014). Determining the Number of Latent Classes in Single- and Multiphase Growth Mixture Models. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(2), 263-279. https://doi.org/10.1080/10705511.2014.882690

Knoef, M., & de Vos, K. (2009). *The Representativeness of LISS, An Online Probability Panel*.

Lagorio, C. (2016). Call and Response: Modelling Longitudinal Contact and Cooperation using Wave 1 Call Records Data. *Understanding Society Working Paper Series, 2016-01*.

Laurie, H., & Lynn, P. (2009). The Use of Respondent Incentives on Longitudinal Studies. In P. Lynn (Ed.), *Methodology of Longitudinal Surveys* (pp. 205-233). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470743874.ch1

Laurie, H., Smith, R., & Scott, L. (2004). Strategies for Reducing Nonresponse in a Longitudinal Panel Survey. *Journal of Official Statistics, 15*.

Lemay, M. (2009). *Understanding the Mechanism of Panel Attrition* [Doctoral Dissertation, University of Maryland,].

Lepkowski, J. M., & Couper, M. P. (2002). Nonresponse in the Second Wave of Longitudinal Household Surveys. In R. M. Groves, D. A. Dillman, J. K. Eltinge, & R. J. A. Little (Eds.), *Survey Nonresponse*. Wiley.

Lipps, O. (2009). Attrition of Households and Individuals in Panel Surveys [Working Paper]. *SOEPpapers on Multidisciplinary Panel Data Research, 164*.

Little, R. J. A., & Rubin, D. B. (2020). *Statistical Analysis with Missing Data* (3rd ed., Vol. 793). Wiley. https://doi.org/10.1002/9781119482260

Little, R. J. A., & Vartivarian, S. (2005). Does Weighting for Nonresponse Increase the Variance of Survey Means? *Survey Methodology*, *31*(2), 161-168.

Lugtig, P. (2014). Panel Attrition: Separating Stayers, Fast Attriters, Gradual Attriters, and Lurkers. *Sociological Methods & Research*, *43*(4), 699-723. https://doi.org/10.1177/0049124113520305

Lugtig, P., Das, M., & Scherpenzeel, A. (2014). Nonresponse and Attrition in a Probability-Based Online Panel for the General Population. In M. B. Callegaro, Reg; Bethleham, Jelke; Göritz, Anja S.; Krosnick, Jon A.; Lavrakas, Paul J. (Ed.), *Online Panel Research* (pp. 135-153). https://doi.org/10.1002/9781118763520.ch6

Luiten, A., Hox, J., & de Leeuw, E. (2020). Survey Nonresponse Trends and Fieldwork Effort in the 21st Century: Results of an International Study across Countries and Surveys. *Journal of Official Statistics, 36*(3), 469-487. https://doi.org/10.2478/jos-2020-0025

Lynn, P. (Ed.). (2006). *Quality Profile: British Household Panel Survey: Waves 1 to 13: 1991 - 2003*. Institute for Social and Economic Research, University of Essex.

Lynn, P. (2009a). Methods for Longitudinal Surveys. In P. Lynn (Ed.), *Methodology of Longitudinal Surveys* (pp. 1-19). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470743874.ch1

Lynn, P. (2009b). Sample Design for *Understanding Society*. *Understanding Society Working Paper Series, 2009-01*.

Lynn, P. (2011a). The Effect of a Mixed Mode Wave on Subsequent Attrition in a Panel Survey: Evidence from the *Understanding Society* Innovation Panel. *Understanding Society Working Paper Series, 2011-06*.

Lynn, P. (2011b). Maintaining Cross-Sectional Representativeness in a Longitudinal General Population Survey. *Understanding Society Working Paper Series, 2011-04*.

Lynn, P. (2013). Targeted Response Inducement Strategies on Longitudinal Surveys. *Understanding Society Working Paper Series, 2013-02*.

Lynn, P. (2017). From standardised to targeted survey procedures for tackling non-response and attrition. *Survey Research Methods, 11*(1). https://doi.org/10.18148/srm/2017.v11i1.6734

Lynn, P. (2018). Tackling Panel Attrition. In D. L. Vannette & J. A. Krosnick (Eds.), *The Palgrave Handbook of Survey Research* (pp. 143-153). Springer International Publishing. https://doi.org/10.1007/978-3-319-54395-6_19

Lynn, P. (2020). Methods for Recruitment and Retention. *Understanding Society Working Paper Series, 2020-07*.

Lynn, P., & Borkowska, M. (2018). Some Indicators of Sample Representativeness and Attrition Bias for BHPS and Understanding Society. *Understanding Society Working Paper Series, 2018-01*.

Lynn, P., Burton, J., Kaminska, O., Knies, G., & Nandi, A. (2012). An Initial Look at Non-Response and Attrition in Understanding Society. *Understanding Society Working Paper Series, 2012-02*.

Lynn, P., & Kaminska, O. (2010). Weighting Strategy for *Understanding Society*. *Understanding Society Working Paper Series, 2010-05*.

Lynn, P., & Knies, G. (Eds.). (2016). *Understanding Society: The UK Household Longitudinal Study Waves 1-5 Quality Profile*. Institute for Social and Economic Research, University of Essex.

Mavletova, A., & Lynn, P. (2017). Data Quality in the Understanding Society Youth Self-Completion Questionnaire. *Understanding Society Working Paper Series, 2017-08*.

Mavletova, A., & Lynn, P. (2019). Item Nonresponse Rates and Panel Conditioning in a Longitudinal Survey among Youth. *Field Methods, 31*(2), 95-115. https://doi.org/10.1177/1525822x18825103

McCutcheon, A. L. (2009). Basic Concepts and Procedures in Single- and Multiple-Group Latent Class Analysis. In J. A. Hagenaars & A. L. McCutcheon (Eds.), *Applied Latent Class Analysis* (pp. 56-88). Cambridge University Press.

Meekins, B. J., & Sangster, R. L. (2004). Predicting Wave Nonresponse from Prior Wave Data Quality. Proceedings of the Annual Meeting of the American Statistical Association,

Moore, J., Burton, J., Crossley, T. F., Fisher, P., Gardiner, C., Jäckle, A., & Benzeval, M. (forthcoming). *Assessing Bias Prevention and Bias Adjustment in a Sub-Annual Online Panel Survey*.

Moore, J., Durrant, G., & Smith, P. (2018). Data Set Representativeness during Data Collection in Three UK Social Surveys: Generalizability and the effects of auxiliary covariate choice. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 181*(1), 229-248. https://doi.org/10.1111/rssa.12256

Moore, J., Durrant, G., & Smith, P. (2021). Do Coefficients of Variation of Response Propensities Approximate Non-Response Biases during Survey Data Collection? *Journal of the Royal Statistical Society: Series A (Statistics in Society), 184*(1), 301-323. https://doi.org/10.1111/rssa.12624

Müller, B., & Castiglioni, L. (2015). Stable Relationships, Stable Participation? The Effects of Partnership Dissolution and Changes in Relationship Stability on Attrition in a Relationship and Family Panel. *Survey Research Methods, 9*(3). https://doi.org/10.18148/srm/2016.v10i1.6207

Nagelkerke, N. J. D. (1991). A Note on a General Definition of the Coefficient of Determination. *Biometrika, 78*(3), 691-692.

Nicolaas, G., Calderwood, L., Lynn, P., & Roberts, C. (2014). *Web Surveys for the General Population: How, why and when?* (National Centre for Research Methods Report, Issue. National Centre for Research Methods. http://eprints.ncrm.ac.uk/3309/

Nishimura, R., Wagner, J., & Elliott, M. (2016). Alternative Indicators for the Risk of Non-Response Bias: A Simulation Study. *International Statistical Review, 84*(1), 43-62. https://doi.org/10.1111/insr.12100

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535-569. https://doi.org/10.1080/10705510701575396

Olson, K., & Witt, L. (2011). Are We Keeping the People Who Used to Stay? Changes in Correlates of Panel Survey Attrition over Time. *Social Science Research, 40*, 1037-1050. https://doi.org/10.1016/j.ssresearch.2011.03.001

Omrani, A., Wakefield-Scurr, J., Smith, J., & Brown, N. (2019). Survey Development for Adolescents Aged 11–16 Years: A developmental science based guide. *Adolescent Research Review, 4*(4), 329-340.

ONS. (2020a). *National Life Tables, England, 1980-1982 to 2017-2019*. https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/nationallifetablesenglandreferencetables/current

ONS. (2020b). *National Life Tables, Scotland, 1980-1982 to 2017-2019*. https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/nationallifetablesscotlandreferencetables

ONS. (2020c). *National Life Tables, Wales, 1980-1982 to 2017-2019*. https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/nationallifetableswalesreferencetables

ONS. (2020d). *RPI: All Items Index: 1947-2020* [.xlsx]. Office for National Statistics. https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceinflation

ONS. (2022). *RPI: All items index: 1947-2022* [.xlsx]. Office for National Statistics. https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceinflation

Onyeaka, H., Anumudu, C. K., Al-Sharify, Z. T., Egele-Godswill, E., & Mbaegbu, P. (2021). COVID-19 Pandemic: A review of the global lockdown and its far-reaching effects. *Science progress, 104*(2).

Peytchev, A., Riley, S., Rosen, J., Murphy, J., & Lindblad, M. (2010). Reduction of Nonresponse Bias in Surveys through Case Prioritization. *Survey Research Methods, 4*(1), 21-29.

Post, A., Gilljam, H., Bremberg, S., & Galanti, M. R. (2012, 2012/05/02). Psychosocial Determinants of Attrition in a Longitudinal Study of Tobacco Use in Youth. *The Scientific World Journal, 2012*, 654030. https://doi.org/10.1100/2012/654030

Prime Minister’s Office. (2020). *Prime Minister's Statement on Coronavirus (COVID-19): 23 March 2020*. Retrieved 12 March 2021 from https://www.gov.uk/government/speeches/pm-address-to-the-nation-on-coronavirus-23-march-2020

Rathje, M., & Glemser, A. (2021). SOEP-Core - 2020: Report of Survey Methodology and Fieldwork. *SOEP Survey Papers 1050: Series B*.

Roberts, C., Vandenplas, C., & Herzing, J. M. E. (2020). A Validation of R-Indicators as a Measure of the Risk of Bias using Data from a Nonresponse Follow-Up Survey. *Journal of Official Statistics, 36*(3), 675-701. https://doi.org/10.2478/jos-2020-0034

Rothenbühler, M., & Voorpostel, M. (2016). Attrition in the Swiss Household Panel: Are Vulnerable Groups more Affected than Others? In M. Oris, C. Roberts, D. Joye, & M. Ernst Stähli (Eds.), *Surveying Human Vulnerabilities across the Life Course* (pp. 223-244). Springer International Publishing. https://doi.org/10.1007/978-3-319-24157-9_10

Rothman, S. (2009). *Estimating Attrition Bias in the Year 9 Cohorts of the Longitudinal Surveys of Australian Youth: Technical Report No. 48*. https://research.acer.edu.au/lsay_technical/48

RStudio Team. (2021). *RStudio: Integrated Development for R.* In (Version 4.0.5) RStudio, PBC.

Rundle-Thiele, S. (2005). Exploring Loyal Qualities: Assessing Survey-Based Loyalty Measures. *Journal of Services Marketing, 19*(7), 492-500. https://doi.org/10.1108/08876040510625990

Sadig, H. (2014). Unknown Eligibility whilst Weighting for Non-response: The Puzzle of who has Died and who is still Alive? *ISER Working Paper Series, 2014-35*.

Sadig, H. (2015). *The Investigation of Alternative Weighting Approaches to Adjust for Non-Response in Longitudinal Surveys* [Doctoral Dissertation, University of Essex]. Colchester.

Särndal, C.-E. (2011). The 2010 Morris Hansen Lecture Dealing with Survey Nonresponse in Data Collection, in Estimation. *Journal of Official Statistics, 27*(1), 1-21.

Sastry, N., McGonagle, K., & Fomby, P. (2020, Jun 4). Effects of the COVID-19 Crisis on Survey Fieldwork: Experience and lessons from two major supplements to the U.S. Panel Study of Income Dynamics. *Survey Research Methods, 14*(2), 241-245. https://doi.org/10.18148/srm/2020.v14i2.7752

Scherpenzeel, A. (2011). Data Collection in a Probability-Based Internet Panel: How the LISS panel was built and how it can be used. *Bulletin of Sociological Methodology, 109*(1), 56-61.

Schonlau, M., & Couper, M. P. (2017). Options for Conducting Web Surveys. *Statistical Science, 32*(2), 279-292. https://doi.org/10.1214/16-STS597

Schonlau, M., van Soest, A., Kapteyn, A., & Couper, M. (2009). Selection Bias in Web Surveys and the Use of Propensity Scores. *Sociological Methods & Research, 37*(3), 291-318. https://doi.org/10.1177/0049124108327128

Schouten, B., Bethlehem, J., Beullens, K., Kleven, Ø., Loosveldt, G., Luiten, A., Rutar, K., Shlomo, N., & Skinner, C. (2012). Evaluating, Comparing, Monitoring, and Improving Representativeness of Survey Response Through R-Indicators and Partial R-Indicators. *International Statistical Review*, *80*(3), 382-399. https://doi.org/10.1111/j.1751-5823.2012.00189.x

Schouten, B., Cobben, F., & Bethlehem, J. (2009). Indicators for the Representativeness of Survey Response. *Survey Methodology, 35*(1), 101-113.

Schouten, B., Cobben, F., Lundquist, P., & Wagner, J. (2016). Does More Balanced Survey Response Imply Less Non-Response Bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society), 179*(3), 727-748. https://doi.org/10.1111/rssa.12152

Schouten, B., Shlomo, N., & Skinner, C. (2011). Indicators for Monitoring and Improving Representativeness of Response. *Journal of Official Statistics, 27*(2), 231-253.

Scott, J. (1997). Children as Respondents: Methods for Improving Data Quality. In L. E. Lyberg, P. P. Biemer, M. Collins, E. D. de Leeuw, C. Dippo, N. Schwarz, & D. Trewin (Eds.), *Survey Measurement and Process Quality*. John Wiley & Sons, Inc. https://doi.org/10.1002/9781118490013.ch14

Scott, J. (2008). Children as Respondents: The Challenge for Quantitative Methods. In P. Christensen & A. James (Eds.), *Research with Children: Perspectives and Practices* (2nd ed., pp. 87-108). Routledge.

Shlomo, N., & Schouten, B. (2013). *Theoretical Properties of Partial Indicators for Representative Response*.

Shlomo, N., Skinner, C., & Schouten, B. (2012). Estimation of an Indicator of the Representativeness of Survey Response. *Journal of Statistical Planning and Inference*, *142*(1), 201-211.

Silverwood, R. J., Calderwood, L., Sakshaug, J. W., & Ploubidis, G. B. (2020). A Data Driven Approach to Understanding and Handling Non-Response in the Next Steps Cohort. *CLS Working Paper, 2020/5*.

Singer, E., & Ye, C. (2013). The Use and Effects of Incentives in Surveys. *The ANNALS of the American Academy of Political and Social Science, 645*(1), 112-141. https://doi.org/10.1177/0002716212458082

Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press.

StataCorp. (2017). *Stata Statistical Software.* In (Version 15) StataCorp LLC.

StataCorp. (2019). *Stata Statistical Software.* In (Version 16) StataCorp LLC.

Statistical Innovations Inc. (2016). *Latent GOLD®*. In (Version 5.1)

Statistical Innovations Inc. (2021). *Latent GOLD®*. In (Version 6)

Thomas, D., Frankenberg, E., & Smith, J. P. (2001). Lost but Not Forgetten: Attrition and Follow-Up in the Indonesia Family Life Survey. *The Journal of Human Resources, 36*(3), 556-592. https://doi.org/10.2307/3069630

Uhrig, S. C. N. (2008). The Nature and Causes of Attrition in the British Household Panel Survey. *ISER Working Paper Series, 2008-05*.

UKHLS. (2019). *Understanding Society: The UK Household Longitudinal Study Waves 1-9 User Guide*.

University of Essex, & Institute for Social and Economic Research. (2019). *Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009* (SN: 6614; Version 12th Edition) [data collection]. UK Data Service. https://doi.org/10.5255/UKDA-SN-6614-13

University of Essex, & Institute for Social and Economic Research. (2021). *Understanding Society: COVID-19 Study, 2020-2021* (SN: 8644; Version 11th Edition) [data collection]. UK Data Service. https://doi.org/10.5255/UKDA-SN-8644-11

University of Essex, & Institute for Social and Economic Research. (2022). *Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009* (SN: 6614; Version 17th Edition) [data collection]. UK Data Service. https://doi.org/10.5255/UKDA-SN-6614-18

Valliant, R., Dever, J. A., & Kreuter, F. (2018). *Practical Tools for Designing and Weighting Survey Samples* (2nd ed.). Springer International Publishing. https://doi.org/10.1007/978-3-319-93632-1

Vermunt, J. K. (2010). Latent Class Modeling with Covariates: Two Improved Three-Step Approaches. *Political Analysis, 18*(4), 450-469. https://doi.org/10.1093/pan/mpq025

Voorpostel, M. (2010). Attrition Patterns in the Swiss Household Panel by Demographic Characteristics and Social Involvement. *Swiss Journal of Sociology, 36*(2), 359-377.

Voorpostel, M., & Lipps, O. (2011). Attrition in the Swiss Household Panel: Is Change Associated with Later Drop-Out. *Journal of Official Statistics, 27*.

Voorpostel, M., Tillmann, R., Lebert, F., Kuhn, U., Lipps, O., Ryser, V.-A., Antal, E., Dasoki, N., & Wernli, B. (2021). *Swiss Household Panel User Guide (1999 - 2021), Wave 23, March 2023*. FORS.

Wagner, J. (2010). The Fraction of Missing Information as a Tool for Monitoring the Quality of Survey Data. *Public Opinion Quarterly, 74*(2), 223-243. https://doi.org/10.1093/poq/nfq007

Watson, N. (2016). Dead or Alive? Dealing with Unknown Eligibility in Longitudinal Surveys. *Journal of Official Statistics*, *32*(4), 987-1010.

Watson, N., Jin, Y., & Summerfield, M. (2021). Wave 20 Data Quality and the Impact of Questionnaire and Fieldwork Changes due to the COVID-19 Pandemic. *HILDA Discussion Paper Series*, *21*(1).

Watson, N., & Wooden, M. (2009). Identifying Factors Affecting Longitudinal Survey Response. In P. Lynn (Ed.), *Methodology of Longitudinal Surveys* (pp. 157-181). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470743874.ch1

Watson, N., & Wooden, M. (2014). Re-engaging with Survey Non-Respondents: Evidence from three household panels. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *177*(2), 499-522. https://doi.org/10.1111/rssa.12024

Winding, T. N., Andersen, J. H., Labriola, M., & Nohr, E. A. (2014). Initial Non-Participation and Loss to Follow-Up in a Danish Youth Cohort: Implications for relative risk estimates. *Journal of Epidemiology and Community Health*, *68*(2), 137-144. https://doi.org/10.1136/jech-2013-202707

Appendix A: Additional Material for Chapter 1

Appendix A: Tables

Table A1: List of covariates and UKHLS specific variable names

Covariates	UKHLS specific variable names
Sex	sex
Age	age_dv
Ethnicity	ethn_dv
Having a Partner	mastat, marstat
Highest Education Qualification	hiqual_dv
Employment Status	jbstat
Self-Rated General Health	hlstat, hlsf1, sf1, scsf1
Monthly Household Net Income	hhneti, fihhmnnet3_dv
Number of Own Children in the Household	nchild_dv
Number of Pensioners in the Household	npens_dv
Dwelling Type	hstype, dweltyp
Housing Tenure	tenure_dv
Household Size	hhsize
Number of Reported Moves	distmov, distmov_dv
Political Support	vote1
Political Interest	vote6

Table A2: Model fit information and statistics for the six best fitting models (unweighted)

Model	Number of Classes	Deviance	*df*	BIC (LL)	Entropy	Class Size (% of sample) Min.	Max.	BLRT
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	**7**	**86,774**	**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

Note: BIC = Bayesian Information Criterion; BLRT = Bootstrapped Likelihood Ratio Test.
N = 9,912.
Deviance = $-2 \times$ Log Likelihood.
The lowest value of the BIC indicates a better fitting model (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). The model shown highlighted in bold typeface was selected as the final model.

Table A3: 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 A4: 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***	(0.05)	0.09	(0.05)	0.04	(0.07)	-0.02	(0.07)
Age (ref: 16-19)								
20-24	-0.16	(0.17)	-0.14	(0.19)	-0.43**	(0.21)	-0.30	(0.20)
25-34	0.05	(0.15)	0.02	(0.15)	-0.26	(0.17)	-0.04	(0.16)
35-44	0.58***	(0.16)	0.17	(0.16)	0.38*	(0.20)	0.07	(0.20)
45-54	1.68***	(0.20)	0.29	(0.18)	0.68***	(0.22)	0.52**	(0.23)
55-64	2.50***	(0.24)	0.56***	(0.17)	1.11***	(0.25)	0.76***	(0.26)
65+	2.92***	(0.23)	-0.14	(0.19)	1.33***	(0.26)	0.89***	(0.27)
Ethnic Minority	0.62***	(0.21)	0.25	(0.20)	0.55**	(0.21)	0.38	(0.24)
Has Partner	-0.49***	(0.08)	0.13	(0.09)	-0.15	(0.09)	0.07	(0.09)
Highest Qualification (ref: No qualification)								
Degree	-1.84***	(0.17)	-0.73***	(0.14)	-1.16***	(0.19)	-0.85***	(0.18)
Other higher degree	-0.96***	(0.15)	-0.34**	(0.13)	-0.89***	(0.19)	-0.43**	(0.19)
A-Level etc.	-0.81***	(0.12)	-0.10	(0.11)	-0.72***	(0.15)	-0.40***	(0.15)
GCSE etc.	-0.66***	(0.11)	-0.17	(0.10)	-0.42***	(0.14)	-0.24*	(0.13)
Other qualification	-0.52***	(0.12)	0.07	(0.12)	-0.27*	(0.14)	-0.08	(0.16)
Job (ref: Employed, in education or training)								
Unemployed	0.59***	(0.21)	-0.19	(0.24)	0.22	(0.22)	-0.21	(0.31)
Retired	-2.66***	(0.15)	-0.55***	(0.13)	-1.60***	(0.15)	-0.89***	(0.17)
Other	-0.70***	(0.14)	-0.50***	(0.13)	-0.68***	(0.16)	-0.52***	(0.17)
Self-rated General Health (ref: Very poor)								
Excellent	2.30***	(0.20)	0.50***	(0.16)	1.01***	(0.20)	1.00***	(0.22)
Good	1.63***	(0.18)	0.28**	(0.14)	0.64***	(0.18)	0.61***	(0.20)
Fair	0.76***	(0.19)	-0.04	(0.14)	0.19	(0.18)	0.33*	(0.18)
Poor	0.30	(0.18)	-0.05	(0.14)	0.04	(0.17)	0.16	(0.21)
Level of interest in politics (ref: Not at all int.)								
Very int.	-0.04	(0.16)	-0.63***	(0.15)	-0.30	(0.19)	-0.29*	(0.18)
Fairly int.	-0.02	(0.11)	-0.38***	(0.10)	-0.17	(0.11)	-0.30**	(0.12)
Not very int.	-0.08	(0.10)	-0.32***	(0.10)	-0.14	(0.10)	-0.25**	(0.12)
Supports a political party	-0.32***	(0.08)	-0.16**	(0.07)	-0.12	(0.09)	-0.54***	(0.10)
Monthly Household Net Income (£000s)	-0.70***	(0.13)	-0.03	(0.06)	-0.10	(0.09)	-0.04	(0.07)
No. of Own Children in the Household	-0.01	(0.08)	-0.14	(0.09)	0.05	(0.10)	0.04	(0.10)
No. of Pensioners in the Household	-0.42***	(0.09)	0.00	(0.07)	-0.45***	(0.10)	-0.28***	(0.10)
Dwelling type (ref: Own entrance)								
Flats and other multi-storey units	0.50***	(0.11)	-0.10	(0.13)	0.42***	(0.14)	-0.00	(0.15)
Bedsits/institutions/other structures	-0.17	(0.25)	-0.02	(0.19)	-0.14	(0.25)	0.09	(0.27)
Own Home	-0.21**	(0.09)	0.04	(0.10)	-0.18	(0.12)	0.02	(0.12)
Household Size	0.58***	(0.05)	0.40***	(0.06)	0.36***	(0.06)	0.36***	(0.06)
No. of Reported Moves	0.92*	(0.48)	1.16***	(0.29)	2.23***	(0.33)	1.82***	(0.31)
Constant	-1.44***	(0.30)	-1.23***	(0.22)	-1.37***	(0.34)	-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. Standard errors in parentheses. * $p < .05$. ** $p < .01$. *** $p < .001$
N = 9,464. Pseudo R^2 = .11

Table A5: 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	(0.18)	-0.39	(0.29)
25-34	-0.31*	(0.18)	-0.51*	(0.27)
35-44	-0.78***	(0.20)	-0.49	(0.31)
45-54	-0.89***	(0.23)	-0.86**	(0.34)
55-64	-0.91***	(0.23)	-0.95**	(0.42)
65+	-2.11***	(0.24)	-2.06***	(0.39)
Ethnic Minority	0.35*	(0.19)	1.16***	(0.34)
Has Partner	-0.46***	(0.09)	-0.37**	(0.17)
Highest Qualification (ref: No qualification)				
Degree	0.02	(0.13)	-0.55*	(0.29)
Other higher degree	0.04	(0.13)	-0.27	(0.27)
A-Level etc.	0.19	(0.12)	-0.36	(0.23)
GCSE etc.	0.17*	(0.10)	-0.10	(0.22)
Other qualification	0.00	(0.13)	-0.10	(0.26)
Job (ref: Employed, in education or training)				
Unemployed	-0.36	(0.23)	0.34	(0.40)
Retired	0.09	(0.15)	-0.33	(0.25)
Other	-0.51***	(0.16)	0.00	(0.23)
Self-rated General Health (ref: Very poor)				
Excellent	-0.61***	(0.17)	-0.33	(0.35)
Good	-0.74***	(0.14)	-0.19	(0.26)
Fair	-0.43***	(0.12)	-0.39	(0.25)
Poor	-0.23*	(0.13)	0.02	(0.29)
Level of interest in politics (ref: Not at all int)				
Very interested	-0.18	(0.14)	0.00	(0.26)
Fairly int	-0.24**	(0.11)	-0.37*	(0.20)
Not very int	-0.15	(0.11)	-0.21	(0.21)
Supports a political party	-0.01	(0.08)	0.03	(0.15)
Monthly Household Net Income (£000s)	0.08	(0.06)	-0.30*	(0.16)
No. of Own Children in the Household	-0.13	(0.09)	-0.09	(0.14)
No. of Pensioners in the Household	0.31***	(0.07)	0.31**	(0.13)
Dwelling type (ref: Own entrance)				
Flats and other multi-storey units	-0.21	(0.13)	0.16	(0.23)
Bedsits/institutions/other structures	-0.02	(0.20)	0.30	(0.44)
Own Home	-0.01	(0.10)	0.34*	(0.19)
Household Size	0.29***	(0.06)	0.27***	(0.10)
No. of Reported Moves	1.10***	(0.27)	1.23**	(0.54)
Constant	-0.40	(0.25)	-1.93***	(0.47)

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. Standard errors in parentheses. * $p < .05$. ** $p < .01$. *** $p < .001$
N = 9,464. Pseudo $R^2 = .11$

Table A6: 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***	(0.78)	-3.41***	(0.96)
C3: Attrition by W22	3.15***	(0.78)	-2.26**	(0.95)
C4: Stayers	2.48***	(0.86)	-1.62*	(0.96)
C5: Attrition by W16	3.34***	(0.81)	-2.70***	(0.94)
C6: Abruptly Nudged	2.45*	(1.32)	-2.39*	(1.23)
Age (ref: 16-19)				
20-24	0.44	(1.30)	0.39	(1.50)
25-34	0.99	(1.01)	-1.56	(1.08)
35-44	0.71	(1.02)	-1.17	(1.16)
45-54	1.74	(1.09)	0.25	(1.13)
55-64	2.94**	(1.16)	-0.46	(1.13)
65+	2.61***	(0.90)	0.41	(0.96)
Ethnic Minority	0.30*	(0.17)	0.05	(0.21)
Self-rated General Health (ref: Very poor)				
Excellent	-0.78***	(0.20)	-1.56***	(0.16)
Good	-0.84***	(0.19)	-1.49***	(0.15)
Fair	-0.47**	(0.18)	-1.27***	(0.16)
Poor	-0.26	(0.21)	-0.56***	(0.17)
No. of Pensioners in the Household	-0.38***	(0.10)	-0.52***	(0.11)

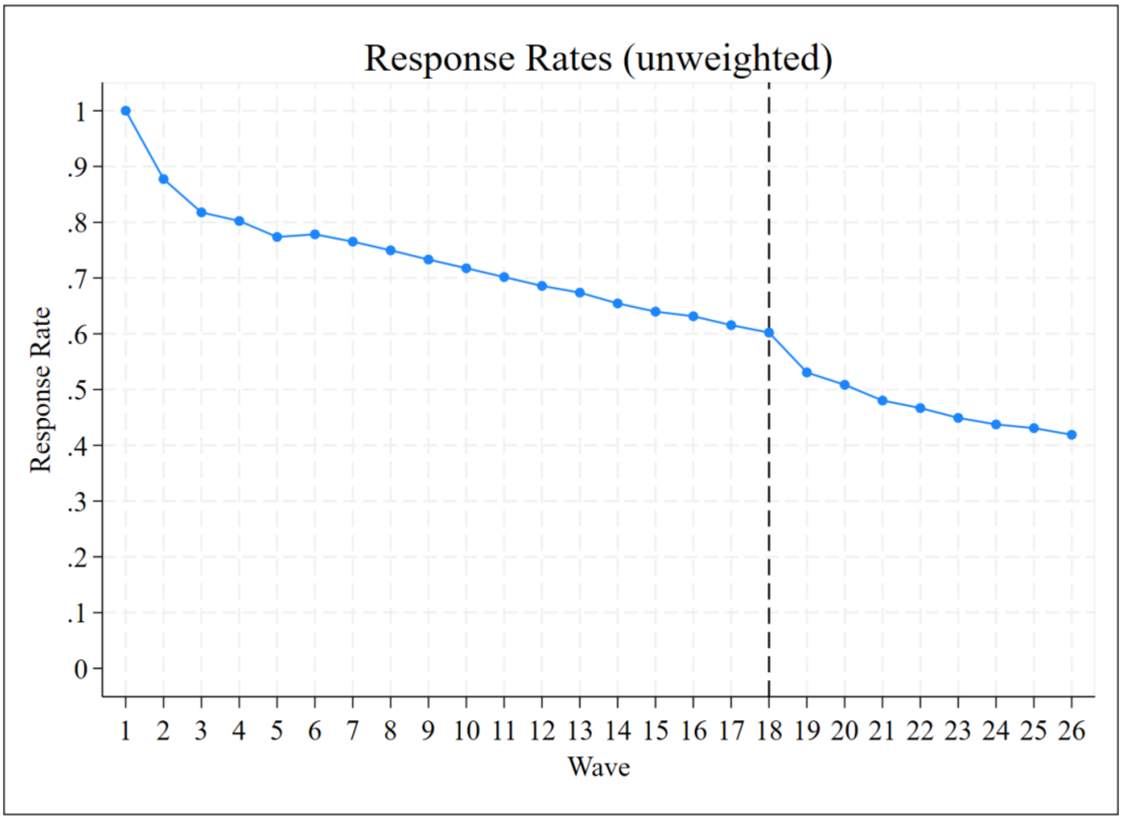
Note: The reference group is Refusal, and the model only contains nonrespondents. This multinomial model has been separated into two tables for readability purposes. The coefficients are rounded to 2 decimal places. Standard errors in parentheses. * $p < .05$. ** $p < .01$. *** $p < .001$
N = 382,999.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

Table A7 (continued): 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) × Age (ref: 16-19)				
C2: Attrition by W8 × 20-24	-0.19	(1.32)	-0.73	(1.55)
C2: Attrition by W8 × 25-34	-1.00	(1.02)	0.80	(1.13)
C2: Attrition by W8 × 35-44	-1.49	(1.01)	0.86	(1.22)
C2: Attrition by W8 × 45-54	-3.32***	(1.07)	-0.24	(1.20)
C2: Attrition by W8 × 55-64	-5.05***	(1.20)	0.78	(1.22)
C2: Attrition by W8 × 65+	-4.56***	(0.91)	2.02**	(0.99)
C3: Attrition by W22 × 20-24	-1.11	(1.31)	-0.95	(1.58)
C3: Attrition by W22 × 25-34	-2.11**	(1.03)	0.39	(1.16)
C3: Attrition by W22 × 35-44	-2.10**	(1.03)	0.01	(1.23)
C3: Attrition by W22 × 45-54	-3.34***	(1.11)	-0.60	(1.20)
C3: Attrition by W22 × 55-64	-3.73***	(1.15)	1.10	(1.15)
C3: Attrition by W22 × 65+	-2.95***	(0.91)	1.10	(1.01)
C4: Stayers × 20-24	-0.18	(1.30)	-0.38	(1.50)
C4: Stayers × 25-34	-0.87	(1.11)	1.14	(1.18)
C4: Stayers × 35-44	-1.12	(1.16)	1.16	(1.21)
C4: Stayers × 45-54	-2.79**	(1.32)	0.17	(1.24)
C4: Stayers × 55-64	-3.17**	(1.27)	1.49	(1.18)
C4: Stayers × 65+	-1.26	(1.13)	2.31**	(1.11)
C5: Attrition by W16 × 20-24	-0.75	(1.37)	-0.88	(1.59)
C5: Attrition by W16 × 25-34	-1.66	(1.04)	1.01	(1.11)
C5: Attrition by W16 × 35-44	-1.84*	(1.03)	0.56	(1.21)
C5: Attrition by W16 × 45-54	-2.91***	(1.04)	-0.30	(1.20)
C5: Attrition by W16 × 55-64	-3.93***	(1.22)	1.92	(1.18)
C5: Attrition by W16 × 65+	-3.78***	(0.95)	2.79***	(1.00)
C6: Abruptly Nudged × 20-24	-0.54	(2.01)	1.10	(1.88)
C6: Abruptly Nudged × 25-34	-0.78	(1.55)	2.13	(1.44)
C6: Abruptly Nudged × 35-44	-0.56	(1.60)	1.55	(1.53)
C6: Abruptly Nudged × 45-54	-1.48	(1.67)	0.59	(1.49)
C6: Abruptly Nudged × 55-64	-3.13*	(1.85)	2.13	(1.51)
C6: Abruptly Nudged × 65+	-2.72	(1.75)	2.87**	(1.30)
Constant	-2.67***	(0.81)	2.61***	(0.92)

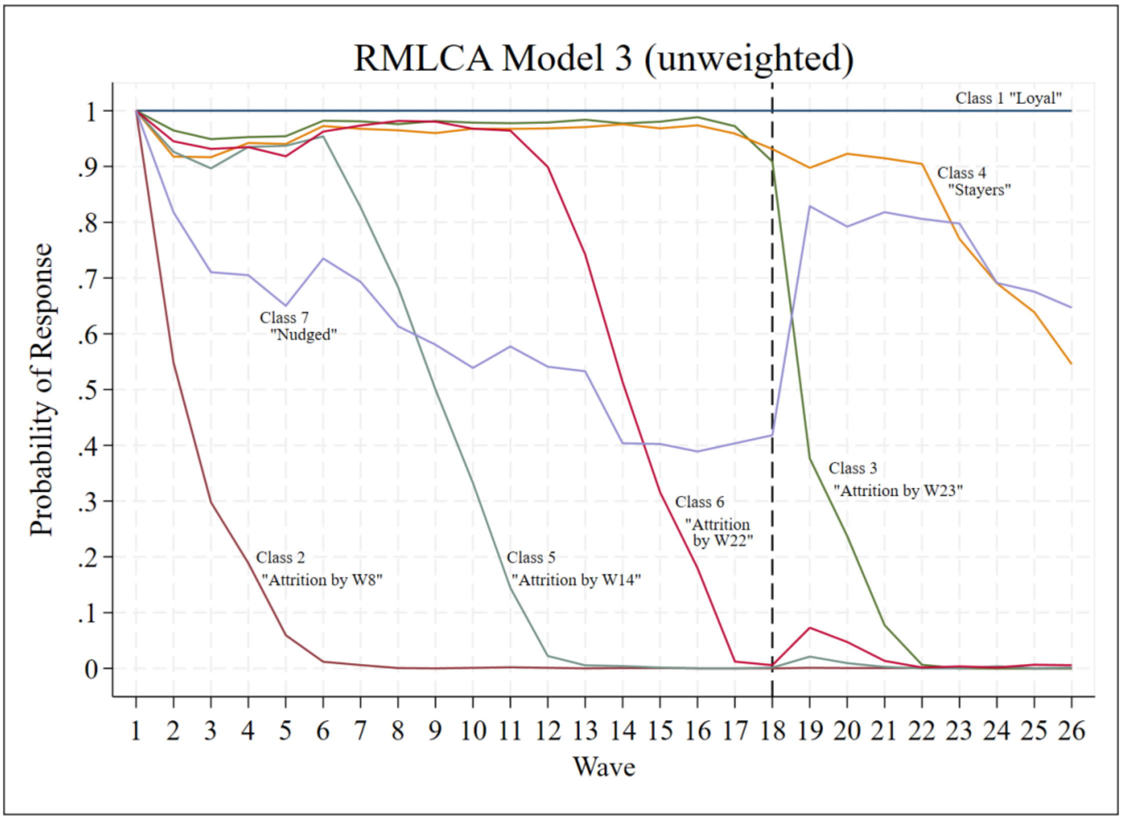
Note: The reference group is Refusal, and the model only contains nonrespondents. This multinomial model has been separated into two tables for readability purposes. The coefficients are rounded to 2 decimal places. Standard errors in parentheses. * $p < .05$. ** $p < .01$. *** $p < .001$
N = 382,999.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

Appendix A: Figures



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.

Figure A1: Overall Response rates (unweighted)



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.

Figure A2: Response probabilities for the unweighted Model 3 (7 Classes)

Appendix B: Additional Material for Chapter 2

Appendix B: Tables

Table B1: Response Rates (RR) for the UKHLS main and COVID-19 datasets, cross-sectional

	Cross-sectional Response Rates	
Wave	MAIN	COVID
2	0.75	0.79
3	0.65	0.76
4	0.59	0.74
5	0.55	0.70
6	0.49	0.64
7	0.46	0.65
8	0.44	0.69
9	0.40	0.66

Note: Response rates are conditional on response to wave 1 and use wave 1 weights.

Table B2: Coefficients of Variation (CV) for the UKHLS main and COVID-19 datasets, cross-sectional

	Cross-sectional CVs	
Wave	MAIN	COVID
2	**0.12 (0.11 - 0.12)**	**0.12 (0.11 - 0.13)**
3	**0.16 (0.16 - 0.17)**	**0.14 (0.13 - 0.15)**
4	**0.19 (0.18 - 0.20)**	**0.15 (0.14 - 0.16)**
5	**0.21 (0.21 - 0.22)**	**0.17 (0.16 - 0.18)**
6	**0.24 (0.23 - 0.25)**	**0.20 (0.19 - 0.21)**
7	**0.26 (0.25 - 0.27)**	**0.21 (0.19 - 0.22)**
8	**0.28 (0.28 - 0.29)**	**0.16 (0.15 - 0.17)**
9	**0.32 (0.30 - 0.33)**	**0.14 (0.13 - 0.15)**

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Table B3: Partial Unconditional Coefficients of Variation (CV_u) for the UKHLS main and COVID-19 datasets, cross-sectional

	Cross-sectional CV_u							
	MAIN				COVID			
Wave	Sex	Ethnicity	Age	Employment Status	Sex	Ethnicity	Age	Employment Status
2	**0.02 (0.01 - 0.02)**	**0.05 (0.04 - 0.05)**	**0.09 (0.08 - 0.09)**	**0.04 (0.03 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.08 (0.07 - 0.09)**	**0.04 (0.03 - 0.05)**
3	**0.03 (0.02 - 0.03)**	**0.06 (0.06 - 0.07)**	**0.11 (0.11 - 0.12)**	**0.04 (0.04 - 0.05)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.11 (0.10 - 0.12)**	**0.06 (0.06 - 0.07)**
4	**0.02 (0.02 - 0.03)**	**0.07 (0.06 - 0.07)**	**0.13 (0.12 - 0.14)**	**0.05 (0.04 - 0.05)**	*0.01 (-0.00 - 0.02)*	**0.04 (0.03 - 0.05)**	**0.13 (0.12 - 0.14)**	**0.07 (0.06 - 0.08)**
5	**0.02 (0.02 - 0.03)**	**0.07 (0.07 - 0.08)**	**0.15 (0.14 - 0.16)**	**0.04 (0.04 - 0.05)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.14 (0.13 - 0.15)**	**0.07 (0.06 - 0.08)**
6	**0.03 (0.02 - 0.04)**	**0.08 (0.07 - 0.09)**	**0.17 (0.16 - 0.18)**	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.04)**	**0.05 (0.04 - 0.07)**	**0.16 (0.15 - 0.17)**	**0.08 (0.07 - 0.09)**
7	**0.02 (0.01 - 0.03)**	**0.08 (0.07 - 0.09)**	**0.18 (0.17 - 0.19)**	**0.07 (0.06 - 0.08)**	**0.04 (0.02 - 0.05)**	**0.06 (0.04 - 0.07)**	**0.17 (0.16 - 0.18)**	**0.11 (0.09 - 0.12)**
8	**0.02 (0.01 - 0.03)**	**0.08 (0.07 - 0.09)**	**0.20 (0.19 - 0.21)**	**0.08 (0.07 - 0.09)**	**0.03 (0.02 - 0.04)**	**0.05 (0.04 - 0.06)**	**0.12 (0.11 - 0.13)**	**0.07 (0.06 - 0.08)**
9	**0.03 (0.01 - 0.04)**	**0.09 (0.08 - 0.10)**	**0.22 (0.21 - 0.23)**	**0.10 (0.09 - 0.12)**	**0.04 (0.02 - 0.05)**	**0.03 (0.02 - 0.05)**	**0.10 (0.09 - 0.11)**	**0.05 (0.04 - 0.06)**
Wave	Household Composition	Marital Status	Highest Qualification	Housing Tenure	Household Composition	Marital Status	Highest Qualification	Housing Tenure
2	**0.05 (0.05 - 0.06)**	**0.07 (0.07 - 0.08)**	**0.02 (0.01 - 0.02)**	**0.06 (0.06 - 0.07)**	**0.06 (0.05 - 0.07)**	**0.06 (0.05 - 0.07)**	**0.04 (0.03 - 0.05)**	**0.04 (0.03 - 0.05)**
3	**0.07 (0.06 - 0.08)**	**0.09 (0.09 - 0.10)**	**0.05 (0.04 - 0.05)**	**0.09 (0.08 - 0.10)**	**0.07 (0.07 - 0.08)**	**0.07 (0.06 - 0.08)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**
4	**0.07 (0.07 - 0.08)**	**0.10 (0.10 - 0.11)**	**0.07 (0.07 - 0.08)**	**0.11 (0.11 - 0.12)**	**0.08 (0.07 - 0.09)**	**0.08 (0.07 - 0.09)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**
5	**0.08 (0.07 - 0.08)**	**0.12 (0.11 - 0.12)**	**0.09 (0.08 - 0.10)**	**0.13 (0.12 - 0.13)**	**0.10 (0.09 - 0.11)**	**0.08 (0.07 - 0.10)**	**0.04 (0.03 - 0.05)**	**0.06 (0.05 - 0.07)**
6	**0.08 (0.07 - 0.09)**	**0.13 (0.12 - 0.14)**	**0.11 (0.10 - 0.12)**	**0.14 (0.13 - 0.15)**	**0.12 (0.11 - 0.13)**	**0.10 (0.09 - 0.11)**	**0.05 (0.03 - 0.06)**	**0.07 (0.06 - 0.08)**
7	**0.08 (0.07 - 0.09)**	**0.13 (0.12 - 0.14)**	**0.13 (0.12 - 0.14)**	**0.15 (0.14 - 0.16)**	**0.13 (0.12 - 0.14)**	**0.10 (0.09 - 0.11)**	**0.03 (0.02 - 0.04)**	**0.08 (0.06 - 0.09)**
8	**0.09 (0.08 - 0.10)**	**0.14 (0.13 - 0.15)**	**0.15 (0.14 - 0.16)**	**0.16 (0.15 - 0.17)**	**0.08 (0.07 - 0.09)**	**0.08 (0.07 - 0.09)**	**0.04 (0.03 - 0.05)**	**0.07 (0.06 - 0.08)**
9	**0.09 (0.08 - 0.10)**	**0.15 (0.14 - 0.16)**	**0.17 (0.16 - 0.18)**	**0.18 (0.17 - 0.19)**	**0.07 (0.06 - 0.08)**	**0.08 (0.07 - 0.09)**	**0.04 (0.03 - 0.05)**	**0.06 (0.05 - 0.07)**

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Table B4: Partial Conditional Coefficients of Variation (CV_c) for the UKHLS main and COVID-19 datasets, cross-sectional

	Cross-sectional CV_c							
	MAIN				COVID			
Wave	Sex	Ethnicity	Age	Employment Status	Sex	Ethnicity	Age	Employment Status
2	**0.01 (0.01 - 0.02)**	**0.03 (0.03 - 0.04)**	**0.04 (0.04 - 0.05)**	**0.01 (0.00 - 0.01)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.01 (0.00 - 0.02)**
3	**0.02 (0.01 - 0.03)**	**0.04 (0.04 - 0.05)**	**0.06 (0.05 - 0.06)**	*0.01 (-0.00 - 0.01)*	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.02)**	**0.05 (0.04 - 0.06)**	**0.01 (0.00 - 0.02)**
4	**0.02 (0.02 - 0.03)**	**0.05 (0.04 - 0.05)**	**0.07 (0.06 - 0.08)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.02)**	**0.06 (0.05 - 0.07)**	**0.01 (0.00 - 0.02)**
5	**0.02 (0.02 - 0.03)**	**0.05 (0.04 - 0.06)**	**0.08 (0.07 - 0.09)**	*0.01 (-0.00 - 0.01)*	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.02)**	**0.07 (0.06 - 0.08)**	*0.01 (-0.00 - 0.02)*
6	**0.03 (0.02 - 0.04)**	**0.06 (0.05 - 0.06)**	**0.09 (0.08 - 0.10)**	*0.01 (-0.00 - 0.02)*	**0.03 (0.02 - 0.05)**	**0.02 (0.01 - 0.03)**	**0.08 (0.06 - 0.09)**	*0.01 (-0.00 - 0.02)*
7	**0.03 (0.02 - 0.04)**	**0.06 (0.05 - 0.07)**	**0.10 (0.09 - 0.11)**	**0.01 (0.00 - 0.02)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.04)**	**0.07 (0.06 - 0.08)**	**0.01 (0.00 - 0.02)**
8	**0.03 (0.02 - 0.04)**	**0.06 (0.05 - 0.07)**	**0.10 (0.09 - 0.11)**	**0.02 (0.01 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.06 (0.05 - 0.07)**	**0.01 (0.00 - 0.02)**
9	**0.04 (0.03 - 0.05)**	**0.07 (0.06 - 0.08)**	**0.12 (0.11 - 0.13)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.01 (0.00 - 0.03)**	**0.04 (0.03 - 0.05)**	*0.01 (-0.00 - 0.02)*
Wave	Household Composition	Marital Status	Highest Qualification	Housing Tenure	Household Composition	Marital Status	Highest Qualification	Housing Tenure
2	**0.03 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.02)**
3	**0.04 (0.03 - 0.05)**	**0.01 (0.01 - 0.02)**	**0.05 (0.04 - 0.05)**	**0.05 (0.04 - 0.06)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.02)**
4	**0.04 (0.03 - 0.05)**	**0.01 (0.01 - 0.02)**	**0.06 (0.05 - 0.07)**	**0.06 (0.05 - 0.07)**	**0.01 (0.01 - 0.02)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.02)**
5	**0.04 (0.03 - 0.04)**	**0.02 (0.01 - 0.02)**	**0.07 (0.06 - 0.08)**	**0.07 (0.06 - 0.08)**	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.03)**
6	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.09 (0.08 - 0.10)**	**0.08 (0.07 - 0.09)**	**0.05 (0.04 - 0.06)**	*0.01 (-0.00 - 0.02)*	**0.06 (0.04 - 0.07)**	**0.02 (0.01 - 0.04)**
7	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.10 (0.09 - 0.11)**	**0.08 (0.07 - 0.09)**	**0.05 (0.03 - 0.06)**	**0.02 (0.01 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**
8	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.11 (0.10 - 0.12)**	**0.09 (0.08 - 0.10)**	**0.03 (0.02 - 0.04)**	*0.01 (-0.00 - 0.02)*	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.04)**
9	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.04)**	**0.11 (0.10 - 0.12)**	**0.10 (0.09 - 0.11)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.04)**	**0.04 (0.02 - 0.05)**	**0.02 (0.01 - 0.03)**

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Table B5: Partial (by category) Unconditional Coefficients of Variation (CV_u) for the UKHLS main and COVID-19 datasets, cross-sectional

Cross-sectional CV_u (by category)

	MAIN				COVID			
Wave	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes
2	**-0.01 (-0.02 - -0.01)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**-0.05 (-0.05 - -0.04)**	*-0.01 (-0.03 - 0.00)*	*0.01 (-0.00 - 0.03)*	**0.01 (0.00 - 0.02)**	**-0.04 (-0.06 - -0.01)**
3	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.02)**	**-0.06 (-0.07 - -0.05)**	**-0.02 (-0.04 - -0.00)**	**0.02 (0.00 - 0.03)**	**0.01 (0.00 - 0.02)**	**-0.03 (-0.06 - -0.01)**
4	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.02)**	**-0.06 (-0.07 - -0.06)**	*-0.01 (-0.02 - 0.01)*	*0.01 (-0.01 - 0.02)*	**0.01 (0.00 - 0.02)**	**-0.04 (-0.06 - -0.01)**
5	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.02)**	**-0.07 (-0.08 - -0.06)**	**-0.02 (-0.03 - -0.00)**	**0.02 (0.00 - 0.03)**	**0.01 (0.00 - 0.02)**	**-0.04 (-0.06 - -0.01)**
6	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**-0.07 (-0.08 - -0.07)**	**-0.02 (-0.04 - -0.00)**	**0.02 (0.00 - 0.04)**	**0.01 (0.01 - 0.02)**	**-0.05 (-0.08 - -0.03)**
7	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**-0.08 (-0.08 - -0.07)**	**-0.03 (-0.04 - -0.01)**	**0.02 (0.01 - 0.04)**	**0.02 (0.01 - 0.02)**	**-0.05 (-0.08 - -0.03)**
8	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**-0.08 (-0.08 - -0.07)**	**-0.02 (-0.04 - -0.01)**	**0.02 (0.01 - 0.04)**	**0.01 (0.01 - 0.02)**	**-0.05 (-0.07 - -0.02)**
9	**-0.02 (-0.02 - -0.01)**	**0.02 (0.01 - 0.02)**	**0.03 (0.03 - 0.03)**	**-0.09 (-0.09 - -0.08)**	**-0.03 (-0.04 - -0.01)**	**0.02 (0.01 - 0.04)**	**0.01 (0.00 - 0.02)**	**-0.03 (-0.06 - -0.01)**

Wave	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44
2	**-0.03 (-0.04 - -0.02)**	**-0.06 (-0.07 - -0.05)**	**-0.03 (-0.03 - -0.02)**	*0.01 (-0.00 - 0.01)*	**-0.05 (-0.07 - -0.03)**	**-0.04 (-0.07 - -0.02)**	*-0.02 (-0.04 - 0.00)*	*-0.00 (-0.02 - 0.01)*
3	**-0.05 (-0.06 - -0.04)**	**-0.07 (-0.08 - -0.07)**	**-0.03 (-0.04 - -0.02)**	**0.01 (0.00 - 0.02)**	**-0.06 (-0.08 - -0.04)**	**-0.05 (-0.07 - -0.02)**	**-0.03 (-0.05 - -0.01)**	*-0.01 (-0.03 - 0.01)*
4	**-0.06 (-0.07 - -0.05)**	**-0.08 (-0.09 - -0.07)**	**-0.03 (-0.04 - -0.02)**	**0.02 (0.01 - 0.03)**	**-0.07 (-0.09 - -0.06)**	**-0.06 (-0.08 - -0.03)**	**-0.04 (-0.06 - -0.02)**	*-0.01 (-0.03 - 0.01)*
5	**-0.07 (-0.08 - -0.06)**	**-0.09 (-0.10 - -0.08)**	**-0.03 (-0.04 - -0.02)**	**0.03 (0.02 - 0.04)**	**-0.08 (-0.09 - -0.06)**	**-0.07 (-0.09 - -0.04)**	**-0.04 (-0.06 - -0.02)**	**-0.02 (-0.04 - -0.01)**
6	**-0.08 (-0.09 - -0.07)**	**-0.09 (-0.10 - -0.08)**	**-0.04 (-0.04 - -0.03)**	**0.03 (0.02 - 0.04)**	**-0.09 (-0.10 - -0.07)**	**-0.07 (-0.09 - -0.05)**	**-0.06 (-0.08 - -0.04)**	**-0.03 (-0.05 - -0.01)**
7	**-0.08 (-0.09 - -0.07)**	**-0.09 (-0.09 - -0.08)**	**-0.02 (-0.03 - -0.02)**	**0.03 (0.02 - 0.04)**	**-0.09 (-0.10 - -0.07)**	**-0.06 (-0.08 - -0.04)**	**-0.06 (-0.08 - -0.05)**	**-0.04 (-0.06 - -0.02)**
8	**-0.08 (-0.09 - -0.07)**	**-0.09 (-0.09 - -0.08)**	**-0.02 (-0.03 - -0.02)**	**0.04 (0.03 - 0.05)**	**-0.06 (-0.08 - -0.04)**	**-0.05 (-0.07 - -0.03)**	**-0.04 (-0.06 - -0.02)**	**-0.03 (-0.05 - -0.01)**
9	**-0.09 (-0.09 - -0.08)**	**-0.08 (-0.09 - -0.07)**	**-0.03 (-0.03 - -0.02)**	**0.04 (0.03 - 0.05)**	**-0.06 (-0.08 - -0.04)**	**-0.05 (-0.07 - -0.02)**	*-0.02 (-0.04 - 0.00)*	*-0.02 (-0.03 - 0.00)*

Wave	Age: 45-54	Age: 55-64	Age: 65+		Age: 45-54	Age: 55-64	Age: 65+	
2	**0.02 (0.02 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.03)**		*0.01 (-0.01 - 0.03)*	**0.04 (0.02 - 0.06)**	*0.02 (-0.01 - 0.04)*	
3	**0.04 (0.03 - 0.04)**	**0.05 (0.04 - 0.06)**	**0.01 (0.00 - 0.02)**		*0.00 (-0.02 - 0.02)*	**0.04 (0.02 - 0.07)**	**0.05 (0.02 - 0.08)**	
4	**0.05 (0.04 - 0.06)**	**0.06 (0.05 - 0.07)**	*-0.01 (-0.01 - 0.00)*		*0.00 (-0.02 - 0.02)*	**0.06 (0.04 - 0.08)**	**0.05 (0.03 - 0.08)**	
5	**0.05 (0.04 - 0.06)**	**0.07 (0.06 - 0.08)**	**-0.02 (-0.03 - -0.01)**		*0.00 (-0.02 - 0.02)*	**0.07 (0.05 - 0.09)**	**0.06 (0.03 - 0.09)**	
6	**0.06 (0.05 - 0.07)**	**0.09 (0.08 - 0.10)**	**-0.03 (-0.04 - -0.02)**		*0.02 (-0.00 - 0.04)*	**0.08 (0.06 - 0.10)**	**0.06 (0.04 - 0.09)**	
7	**0.07 (0.06 - 0.08)**	**0.09 (0.08 - 0.10)**	**-0.05 (-0.06 - -0.05)**		*0.01 (-0.01 - 0.03)*	**0.07 (0.05 - 0.10)**	**0.08 (0.05 - 0.11)**	
8	**0.08 (0.07 - 0.09)**	**0.11 (0.10 - 0.12)**	**-0.08 (-0.08 - -0.07)**		*0.01 (-0.01 - 0.03)*	**0.07 (0.05 - 0.09)**	**0.04 (0.02 - 0.06)**	
9	**0.09 (0.08 - 0.10)**	**0.12 (0.11 - 0.13)**	**-0.10 (-0.10 - -0.09)**		*0.01 (-0.01 - 0.03)*	**0.05 (0.03 - 0.07)**	**0.03 (0.00 - 0.05)**	

Table B5 continued on next page.

Table B5 cont.

Wave	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other
2	**-0.01 (-0.01 - -0.00)**	**-0.03 (-0.03 - -0.02)**	**0.03 (0.02 - 0.04)**	*-0.00 (-0.01 - 0.01)*	*-0.00 (-0.02 - 0.01)*	*-0.02 (-0.05 - 0.01)*	**0.02 (0.00 - 0.05)**	*-0.02 (-0.05 - 0.01)*
3	*-0.00 (-0.01 - 0.00)*	**-0.03 (-0.04 - -0.02)**	**0.03 (0.02 - 0.03)**	*-0.01 (-0.01 - 0.00)*	**-0.02 (-0.04 - -0.01)**	*-0.03 (-0.06 - 0.00)*	**0.05 (0.03 - 0.08)**	*-0.01 (-0.04 - 0.02)*
4	**0.01 (0.00 - 0.01)**	**-0.04 (-0.05 - -0.03)**	**0.01 (0.00 - 0.02)**	**-0.01 (-0.02 - -0.00)**	**-0.02 (-0.04 - -0.01)**	*-0.03 (-0.06 - 0.00)*	**0.06 (0.04 - 0.08)**	*-0.01 (-0.04 - 0.02)*
5	**0.02 (0.01 - 0.02)**	**-0.04 (-0.05 - -0.03)**	*0.00 (-0.01 - 0.01)*	**-0.01 (-0.02 - -0.00)**	**-0.03 (-0.04 - -0.01)**	*-0.02 (-0.05 - 0.01)*	**0.06 (0.04 - 0.09)**	*-0.01 (-0.04 - 0.02)*
6	**0.02 (0.02 - 0.03)**	**-0.05 (-0.05 - -0.04)**	*-0.00 (-0.01 - 0.00)*	**-0.01 (-0.02 - -0.01)**	**-0.03 (-0.05 - -0.02)**	*-0.03 (-0.06 - 0.00)*	**0.07 (0.04 - 0.09)**	*-0.01 (-0.04 - 0.02)*
7	**0.04 (0.03 - 0.04)**	**-0.05 (-0.05 - -0.04)**	**-0.03 (-0.03 - -0.02)**	**-0.02 (-0.03 - -0.01)**	**-0.04 (-0.06 - -0.03)**	**-0.03 (-0.06 - -0.00)**	**0.09 (0.07 - 0.12)**	*-0.01 (-0.04 - 0.02)*
8	**0.05 (0.04 - 0.05)**	**-0.05 (-0.05 - -0.04)**	**-0.05 (-0.05 - -0.04)**	**-0.02 (-0.03 - -0.01)**	**-0.02 (-0.03 - -0.00)**	**-0.03 (-0.06 - -0.00)**	**0.05 (0.03 - 0.08)**	*-0.02 (-0.05 - 0.01)*
9	**0.06 (0.06 - 0.07)**	**-0.05 (-0.06 - -0.04)**	**-0.06 (-0.07 - -0.05)**	**-0.03 (-0.03 - -0.02)**	*-0.01 (-0.03 - 0.00)*	*-0.02 (-0.05 - 0.01)*	**0.04 (0.02 - 0.06)**	*-0.02 (-0.05 - 0.01)*

Wave	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children
2	*-0.00 (-0.01 - 0.01)*	*-0.00 (-0.01 - 0.01)*	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**	*0.01 (-0.02 - 0.03)*	*-0.01 (-0.04 - 0.01)*	**0.04 (0.02 - 0.06)**	*-0.01 (-0.02 - 0.01)*
3	*0.00 (-0.01 - 0.01)*	*-0.00 (-0.01 - 0.01)*	**0.04 (0.03 - 0.04)**	**0.02 (0.01 - 0.03)**	*0.01 (-0.02 - 0.03)*	*-0.02 (-0.05 - 0.01)*	**0.06 (0.04 - 0.07)**	**-0.02 (-0.04 - -0.00)**
4	*-0.00 (-0.01 - 0.01)*	**-0.01 (-0.02 - -0.00)**	**0.04 (0.03 - 0.05)**	**0.02 (0.02 - 0.03)**	*0.02 (-0.01 - 0.04)*	*-0.02 (-0.05 - 0.00)*	**0.06 (0.04 - 0.08)**	**-0.02 (-0.04 - -0.01)**
5	*-0.01 (-0.02 - 0.00)*	**-0.01 (-0.02 - -0.00)**	**0.04 (0.03 - 0.05)**	**0.03 (0.02 - 0.04)**	*0.01 (-0.01 - 0.04)*	**-0.03 (-0.05 - -0.00)**	**0.07 (0.05 - 0.09)**	**-0.04 (-0.06 - -0.02)**
6	**-0.01 (-0.02 - -0.00)**	**-0.02 (-0.03 - -0.01)**	**0.04 (0.04 - 0.05)**	**0.03 (0.02 - 0.03)**	*0.02 (-0.01 - 0.04)*	**-0.04 (-0.06 - -0.02)**	**0.09 (0.07 - 0.11)**	**-0.06 (-0.07 - -0.04)**
7	**-0.02 (-0.03 - -0.01)**	**-0.02 (-0.03 - -0.01)**	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.03)**	*0.02 (-0.00 - 0.05)*	**-0.05 (-0.07 - -0.02)**	**0.09 (0.07 - 0.11)**	**-0.07 (-0.08 - -0.05)**
8	**-0.03 (-0.04 - -0.02)**	**-0.02 (-0.03 - -0.02)**	**0.05 (0.05 - 0.06)**	**0.03 (0.02 - 0.04)**	*0.00 (-0.02 - 0.03)*	**-0.03 (-0.06 - -0.01)**	**0.06 (0.04 - 0.08)**	**-0.04 (-0.05 - -0.02)**
9	**-0.04 (-0.05 - -0.03)**	**-0.03 (-0.04 - -0.02)**	**0.05 (0.04 - 0.06)**	**0.04 (0.03 - 0.04)**	*0.00 (-0.02 - 0.03)*	**-0.03 (-0.05 - -0.00)**	**0.06 (0.04 - 0.08)**	**-0.02 (-0.04 - -0.00)**

Wave	HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children			HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children		
2	**-0.04 (-0.04 - -0.03)**	**-0.02 (-0.03 - -0.01)**			**-0.03 (-0.05 - -0.00)**	**-0.03 (-0.05 - -0.01)**		
3	**-0.05 (-0.06 - -0.04)**	**-0.03 (-0.04 - -0.02)**			*-0.02 (-0.04 - 0.01)*	**-0.04 (-0.06 - -0.02)**		
4	**-0.05 (-0.06 - -0.04)**	**-0.03 (-0.04 - -0.02)**			*-0.02 (-0.04 - 0.00)*	**-0.04 (-0.06 - -0.02)**		
5	**-0.05 (-0.06 - -0.04)**	**-0.03 (-0.04 - -0.02)**			*-0.02 (-0.05 - 0.00)*	**-0.04 (-0.06 - -0.01)**		
6	**-0.04 (-0.05 - -0.03)**	**-0.03 (-0.04 - -0.02)**			*-0.02 (-0.04 - 0.01)*	**-0.04 (-0.06 - -0.02)**		
7	**-0.04 (-0.05 - -0.03)**	**-0.03 (-0.04 - -0.02)**			*-0.01 (-0.03 - 0.01)*	**-0.04 (-0.06 - -0.02)**		
8	**-0.04 (-0.05 - -0.03)**	**-0.03 (-0.04 - -0.02)**			*-0.00 (-0.02 - 0.02)*	**-0.03 (-0.05 - -0.01)**		
9	**-0.04 (-0.04 - -0.03)**	**-0.03 (-0.04 - -0.02)**			*-0.02 (-0.04 - 0.01)*	**-0.03 (-0.05 - -0.01)**		

Table B5 continued on next page.

Table B5 cont.

Wave	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed
2	**-0.06 (-0.06 - -0.05)**	**0.04 (0.03 - 0.04)**	**0.02 (0.01 - 0.02)**	*0.01 (-0.00 - 0.02)*	**-0.04 (-0.06 - -0.02)**	**0.03 (0.02 - 0.05)**	*0.02 (-0.01 - 0.04)*	*-0.02 (-0.05 - 0.01)*
3	**-0.08 (-0.08 - -0.07)**	**0.05 (0.05 - 0.06)**	**0.03 (0.02 - 0.04)**	*-0.00 (-0.01 - 0.01)*	**-0.06 (-0.07 - -0.04)**	**0.04 (0.02 - 0.05)**	*0.01 (-0.01 - 0.04)*	*0.00 (-0.03 - 0.04)*
4	**-0.08 (-0.09 - -0.07)**	**0.06 (0.05 - 0.06)**	**0.03 (0.02 - 0.04)**	**-0.01 (-0.02 - -0.00)**	**-0.06 (-0.08 - -0.04)**	**0.04 (0.03 - 0.06)**	*0.02 (-0.01 - 0.05)*	*-0.01 (-0.04 - 0.02)*
5	**-0.09 (-0.09 - -0.08)**	**0.07 (0.06 - 0.07)**	**0.03 (0.02 - 0.04)**	**-0.02 (-0.03 - -0.01)**	**-0.07 (-0.09 - -0.05)**	**0.04 (0.03 - 0.06)**	*0.02 (-0.00 - 0.05)*	*0.00 (-0.03 - 0.04)*
6	**-0.10 (-0.10 - -0.09)**	**0.08 (0.07 - 0.08)**	**0.03 (0.02 - 0.04)**	**-0.03 (-0.04 - -0.03)**	**-0.08 (-0.10 - -0.07)**	**0.05 (0.03 - 0.07)**	**0.03 (0.00 - 0.06)**	*0.01 (-0.02 - 0.04)*
7	**-0.09 (-0.09 - -0.08)**	**0.08 (0.07 - 0.08)**	**0.03 (0.02 - 0.04)**	**-0.05 (-0.06 - -0.04)**	**-0.08 (-0.10 - -0.06)**	**0.05 (0.03 - 0.07)**	**0.03 (0.00 - 0.06)**	*0.00 (-0.03 - 0.04)*
8	**-0.09 (-0.10 - -0.08)**	**0.09 (0.08 - 0.09)**	**0.03 (0.02 - 0.04)**	**-0.06 (-0.07 - -0.06)**	**-0.06 (-0.08 - -0.04)**	**0.04 (0.02 - 0.05)**	*0.02 (-0.01 - 0.05)*	*0.01 (-0.03 - 0.04)*
9	**-0.09 (-0.10 - -0.08)**	**0.09 (0.08 - 0.10)**	**0.03 (0.02 - 0.04)**	**-0.07 (-0.08 - -0.07)**	**-0.06 (-0.08 - -0.05)**	**0.05 (0.03 - 0.06)**	*0.02 (-0.01 - 0.04)*	*-0.01 (-0.04 - 0.02)*

Wave	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE
2	**-0.01 (-0.02 - -0.00)**	**0.01 (0.01 - 0.02)**	**-0.01 (-0.02 - -0.00)**	*-0.00 (-0.01 - 0.01)*	*-0.03 (-0.06 - 0.01)*	**0.02 (0.01 - 0.04)**	*-0.00 (-0.02 - 0.02)*	*0.00 (-0.02 - 0.02)*
3	**-0.03 (-0.04 - -0.02)**	**0.04 (0.03 - 0.04)**	**-0.01 (-0.02 - -0.00)**	**-0.01 (-0.02 - -0.00)**	*-0.01 (-0.04 - 0.03)*	**0.02 (0.00 - 0.04)**	*-0.01 (-0.03 - 0.01)*	*-0.02 (-0.04 - 0.01)*
4	**-0.05 (-0.06 - -0.04)**	**0.05 (0.05 - 0.06)**	*-0.01 (-0.01 - 0.00)*	**-0.01 (-0.02 - -0.01)**	*-0.00 (-0.04 - 0.03)*	*0.01 (-0.00 - 0.03)*	*-0.01 (-0.03 - 0.01)*	*-0.01 (-0.03 - 0.01)*
5	**-0.06 (-0.07 - -0.06)**	**0.06 (0.06 - 0.07)**	**-0.01 (-0.02 - -0.00)**	**-0.01 (-0.02 - -0.00)**	*-0.01 (-0.05 - 0.02)*	**0.03 (0.01 - 0.05)**	*-0.01 (-0.03 - 0.01)*	**-0.03 (-0.05 - -0.01)**
6	**-0.07 (-0.08 - -0.07)**	**0.08 (0.07 - 0.09)**	**-0.01 (-0.02 - -0.00)**	**-0.02 (-0.03 - -0.01)**	*-0.03 (-0.07 - 0.00)*	**0.03 (0.01 - 0.04)**	*-0.01 (-0.03 - 0.01)*	*-0.00 (-0.02 - 0.02)*
7	**-0.09 (-0.10 - -0.09)**	**0.09 (0.09 - 0.10)**	**-0.01 (-0.02 - -0.00)**	**-0.01 (-0.02 - -0.01)**	*0.00 (-0.04 - 0.04)*	**0.02 (0.00 - 0.04)**	*-0.01 (-0.03 - 0.01)*	*-0.01 (-0.03 - 0.01)*
8	**-0.11 (-0.11 - -0.10)**	**0.11 (0.10 - 0.11)**	*-0.01 (-0.02 - 0.00)*	**-0.01 (-0.02 - -0.01)**	*-0.01 (-0.04 - 0.03)*	**0.03 (0.01 - 0.04)**	*-0.01 (-0.03 - 0.01)*	*-0.02 (-0.04 - 0.00)*
9	**-0.12 (-0.13 - -0.11)**	**0.11 (0.11 - 0.12)**	*-0.00 (-0.01 - 0.01)*	**-0.02 (-0.03 - -0.01)**	*-0.01 (-0.04 - 0.03)*	**0.03 (0.01 - 0.05)**	*-0.01 (-0.03 - 0.01)*	*-0.02 (-0.04 - 0.00)*

Wave	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other
2	*0.00 (-0.01 - 0.01)*	**0.03 (0.03 - 0.04)**	**-0.05 (-0.06 - -0.05)**	*-0.00 (-0.01 - 0.01)*	*-0.02 (-0.05 - 0.01)*	**0.02 (0.01 - 0.04)**	**-0.03 (-0.06 - -0.01)**	*-0.00 (-0.02 - 0.01)*
3	*0.00 (-0.01 - 0.01)*	**0.05 (0.05 - 0.05)**	**-0.08 (-0.08 - -0.07)**	**-0.01 (-0.02 - -0.00)**	*0.01 (-0.02 - 0.04)*	**0.02 (0.01 - 0.04)**	**-0.04 (-0.06 - -0.01)**	*-0.00 (-0.02 - 0.01)*
4	*-0.00 (-0.01 - 0.01)*	**0.06 (0.06 - 0.07)**	**-0.10 (-0.10 - -0.09)**	*-0.01 (-0.02 - 0.00)*	*0.00 (-0.03 - 0.03)*	**0.02 (0.01 - 0.04)**	**-0.04 (-0.06 - -0.01)**	*0.01 (-0.01 - 0.02)*
5	*-0.00 (-0.01 - 0.01)*	**0.07 (0.07 - 0.07)**	**-0.10 (-0.11 - -0.10)**	**-0.01 (-0.02 - -0.00)**	*0.00 (-0.03 - 0.03)*	**0.03 (0.02 - 0.04)**	**-0.05 (-0.07 - -0.02)**	*0.01 (-0.01 - 0.03)*
6	*-0.01 (-0.02 - 0.00)*	**0.08 (0.08 - 0.08)**	**-0.12 (-0.13 - -0.11)**	**-0.01 (-0.02 - -0.00)**	*-0.01 (-0.04 - 0.02)*	**0.04 (0.02 - 0.05)**	**-0.06 (-0.08 - -0.04)**	*0.01 (-0.01 - 0.03)*
7	**-0.02 (-0.03 - -0.01)**	**0.08 (0.08 - 0.09)**	**-0.13 (-0.13 - -0.12)**	**-0.01 (-0.02 - -0.00)**	*-0.00 (-0.03 - 0.03)*	**0.04 (0.03 - 0.06)**	**-0.06 (-0.09 - -0.04)**	*0.01 (-0.01 - 0.03)*
8	**-0.02 (-0.03 - -0.01)**	**0.09 (0.09 - 0.09)**	**-0.13 (-0.14 - -0.13)**	**-0.02 (-0.03 - -0.01)**	*-0.01 (-0.04 - 0.02)*	**0.04 (0.02 - 0.05)**	**-0.06 (-0.08 - -0.04)**	*0.00 (-0.01 - 0.02)*
9	**-0.02 (-0.03 - -0.01)**	**0.10 (0.10 - 0.10)**	**-0.15 (-0.16 - -0.14)**	**-0.01 (-0.02 - -0.01)**	*-0.02 (-0.05 - 0.01)*	**0.03 (0.02 - 0.05)**	**-0.05 (-0.07 - -0.03)**	*0.00 (-0.01 - 0.02)*

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.
Abbrev.: Employment Status – Emp Stat; Employed, In Education or Training – Emp, In Educ or Training; Household Composition – HH Comp; Marital Status – Mar Stat; Highest Qualification – High Qual; Housing Tenure – Tenure

Table B6: Partial (by category) Conditional Coefficients of Variation (CV_c) for the UKHLS main and COVID-19 datasets, cross-sectional

Cross-sectional CVc (by category)

	MAIN				COVID			
Wave	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes
2	**0.01 (0.01 - 0.01)**	**0.01 (0.01 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.03 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**
3	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.02)**	**0.04 (0.03 - 0.04)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**
4	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.02)**	**0.04 (0.04 - 0.05)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**
5	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.02)**	**0.05 (0.04 - 0.05)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**
6	**0.02 (0.01 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.05 (0.04 - 0.06)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.02 (0.01 - 0.03)**
7	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.03)**
8	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.05 (0.05 - 0.06)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.03)**
9	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.03 (0.03 - 0.03)**	**0.06 (0.06 - 0.07)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**
Wave	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44
2	**0.01 (0.00 - 0.01)**	**0.02 (0.02 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**
3	**0.01 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**
4	**0.02 (0.01 - 0.02)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**
5	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.03 (0.03 - 0.04)**	**0.03 (0.02 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**
6	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.03 (0.03 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.03 (0.02 - 0.03)**
7	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.03 (0.03 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.02 (0.02 - 0.03)**
8	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.03 (0.03 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**
9	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.03 (0.03 - 0.04)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**
Wave	Age: 45-54	Age: 55-64	Age: 65+		Age: 45-54	Age: 55-64	Age: 65+	
2	**0.02 (0.02 - 0.02)**	**0.02 (0.02 - 0.02)**	**0.01 (0.00 - 0.01)**		**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.00 (0.00 - 0.01)**	
3	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.01 (0.01 - 0.01)**		**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	
4	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.02 (0.01 - 0.02)**		**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.01 (0.01 - 0.01)**	
5	**0.03 (0.03 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.02 (0.02 - 0.03)**		**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.01 (0.01 - 0.02)**	
6	**0.03 (0.03 - 0.04)**	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.03)**		**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.01 (0.01 - 0.02)**	
7	**0.04 (0.03 - 0.04)**	**0.05 (0.05 - 0.06)**	**0.03 (0.03 - 0.04)**		**0.03 (0.03 - 0.04)**	**0.03 (0.03 - 0.04)**	**0.01 (0.00 - 0.01)**	
8	**0.04 (0.03 - 0.04)**	**0.06 (0.06 - 0.07)**	**0.04 (0.03 - 0.05)**		**0.02 (0.02 - 0.03)**	**0.04 (0.03 - 0.04)**	**0.01 (0.01 - 0.01)**	
9	**0.04 (0.03 - 0.05)**	**0.07 (0.06 - 0.08)**	**0.05 (0.04 - 0.06)**		**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.01)**	

Table B6 continued on the next page.

Table B6 cont.

Wave	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other
2	**0.00 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.00 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**
3	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*
4	**0.00 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*
5	*0.00 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.04 - 0.04)*	*0.01 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*
6	*0.00 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.00 (-0.03 - 0.03)*	*0.01 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*
7	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.02)*	*0.01 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.02)*	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*
8	**0.01 (0.01 - 0.02)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.00 - 0.02)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*
9	**0.02 (0.01 - 0.02)**	*0.01 (-0.00 - 0.02)*	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.02)**	*0.01 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.02)*

Wave	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children
2	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.02 (0.01 - 0.02)**	**0.00 (0.00 - 0.01)**
3	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.02 - 0.02)**	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	**0.01 (0.01 - 0.02)**	**0.00 (0.00 - 0.01)**
4	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**	*0.01 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.02)**	*0.00 (-0.00 - 0.01)*
5	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**	*0.00 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.02)**
6	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.02 (0.02 - 0.03)**
7	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.03)**
8	**0.01 (0.00 - 0.02)**	*0.00 (-0.00 - 0.01)*	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**
9	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.01)*	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**

Wave	HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children	HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children
2	**0.02 (0.02 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**
3	**0.03 (0.02 - 0.03)**	**0.01 (0.01 - 0.01)**	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*
4	**0.03 (0.03 - 0.04)**	**0.01 (0.01 - 0.01)**	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*
5	**0.03 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	*0.01 (-0.00 - 0.01)*
6	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**
7	**0.03 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**
8	**0.03 (0.02 - 0.03)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**
9	**0.03 (0.02 - 0.03)**	*0.01 (-0.00 - 0.02)*	**0.01 (0.00 - 0.02)**	*0.01 (-0.00 - 0.01)*

Table B6 continued on the next page.

Table B6 cont.

Wave	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed
2	**0.00 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**
3	**0.01 (0.00 - 0.01)**	**0.00 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.00 (0.00 - 0.01)**	**0.00 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**
4	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.03)**
5	**0.01 (0.00 - 0.01)**	**0.00 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*	**0.00 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**
6	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.02)**	*0.01 (-0.00 - 0.01)*
7	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**
8	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	*0.00 (-0.01 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*
9	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**

Wave	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE
2	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**
3	**0.03 (0.03 - 0.04)**	**0.03 (0.02 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.02)**
4	**0.04 (0.04 - 0.05)**	**0.04 (0.03 - 0.04)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**
5	**0.05 (0.04 - 0.06)**	**0.04 (0.04 - 0.05)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.02 (0.02 - 0.03)**
6	**0.06 (0.05 - 0.06)**	**0.06 (0.05 - 0.06)**	**0.02 (0.02 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**
7	**0.06 (0.05 - 0.07)**	**0.06 (0.06 - 0.07)**	**0.02 (0.02 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**
8	**0.07 (0.06 - 0.08)**	**0.07 (0.06 - 0.08)**	**0.02 (0.02 - 0.02)**	**0.03 (0.02 - 0.03)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.02)**
9	**0.07 (0.06 - 0.08)**	**0.07 (0.06 - 0.08)**	**0.02 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	*0.01 (-0.00 - 0.01)*	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**

Wave	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other
2	**0.01 (0.00 - 0.01)**	**0.02 (0.02 - 0.02)**	**0.02 (0.02 - 0.03)**	*0.00 (-0.00 - 0.01)*	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.01)*
3	**0.01 (0.01 - 0.02)**	**0.03 (0.03 - 0.03)**	**0.04 (0.03 - 0.04)**	**0.01 (0.00 - 0.02)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.01)*
4	**0.02 (0.01 - 0.02)**	**0.04 (0.03 - 0.04)**	**0.05 (0.04 - 0.05)**	*0.01 (-0.00 - 0.01)*	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.01)*
5	**0.02 (0.01 - 0.02)**	**0.04 (0.04 - 0.04)**	**0.05 (0.05 - 0.06)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.02)**	*0.00 (-0.01 - 0.01)*
6	**0.02 (0.02 - 0.03)**	**0.04 (0.04 - 0.05)**	**0.06 (0.05 - 0.07)**	*0.01 (-0.00 - 0.02)*	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	*0.01 (-0.00 - 0.02)*
7	**0.03 (0.02 - 0.04)**	**0.05 (0.04 - 0.05)**	**0.07 (0.06 - 0.07)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	*0.00 (-0.01 - 0.02)*
8	**0.03 (0.02 - 0.04)**	**0.05 (0.05 - 0.06)**	**0.07 (0.06 - 0.08)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	*0.00 (-0.03 - 0.03)*
9	**0.03 (0.02 - 0.04)**	**0.06 (0.05 - 0.06)**	**0.08 (0.07 - 0.09)**	**0.01 (0.00 - 0.02)**	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	*0.00 (-0.07 - 0.07)*

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.
Abbrev.: Employment Status – Emp Stat; Employed, In Education or Training – Emp, In Educ or Training; Household Composition – HH Comp; Marital Status – Mar Stat; Highest Qualification – High Qual; Housing Tenure – Tenure

Table B7: Response Rates (RR) for the UKHLS main and COVID-19 datasets, longitudinal

	Longitudinal Response Rates	
Wave	MAIN	COVID
3	0.61	0.71
4	0.53	0.65
5	0.48	0.60
6	0.41	0.54
7	0.37	0.50
8	0.34	0.48
9	0.30	0.44

Note: Response rates are conditional on response to wave 1 and 2 and use wave 1 weights

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Table B8: Partial Unconditional Coefficients of Variation (CV_u) for the UKHLS main and COVID-19 datasets, longitudinal

	Longitudinal CV_u							
	MAIN				COVID			
Wave	Sex	Ethnicity	Age	Employment Status	Sex	Ethnicity	Age	Employment Status
3	**0.03 (0.02 - 0.04)**	**0.08 (0.07 - 0.09)**	**0.14 (0.13 - 0.14)**	**0.06 (0.05 - 0.06)**	**0.03 (0.02 - 0.04)**	**0.05 (0.04 - 0.06)**	**0.11 (0.10 - 0.13)**	**0.08 (0.07 - 0.09)**
4	**0.04 (0.03 - 0.04)**	**0.09 (0.08 - 0.10)**	**0.17 (0.16 - 0.18)**	**0.06 (0.05 - 0.07)**	**0.02 (0.01 - 0.03)**	**0.07 (0.06 - 0.08)**	**0.15 (0.14 - 0.16)**	**0.10 (0.08 - 0.11)**
5	**0.04 (0.03 - 0.05)**	**0.11 (0.10 - 0.11)**	**0.20 (0.19 - 0.21)**	**0.06 (0.05 - 0.07)**	**0.03 (0.01 - 0.04)**	**0.08 (0.06 - 0.09)**	**0.18 (0.17 - 0.19)**	**0.11 (0.10 - 0.12)**
6	**0.04 (0.03 - 0.05)**	**0.11 (0.10 - 0.12)**	**0.23 (0.22 - 0.24)**	**0.07 (0.06 - 0.08)**	**0.03 (0.01 - 0.04)**	**0.09 (0.07 - 0.10)**	**0.22 (0.20 - 0.23)**	**0.14 (0.12 - 0.15)**
7	**0.04 (0.03 - 0.05)**	**0.12 (0.11 - 0.13)**	**0.25 (0.24 - 0.26)**	**0.07 (0.06 - 0.08)**	**0.03 (0.01 - 0.04)**	**0.09 (0.08 - 0.11)**	**0.24 (0.22 - 0.26)**	**0.16 (0.15 - 0.18)**
8	**0.04 (0.03 - 0.05)**	**0.13 (0.11 - 0.14)**	**0.27 (0.26 - 0.28)**	**0.07 (0.06 - 0.09)**	**0.03 (0.01 - 0.04)**	**0.10 (0.08 - 0.12)**	**0.24 (0.22 - 0.26)**	**0.16 (0.14 - 0.18)**
9	**0.04 (0.03 - 0.06)**	**0.13 (0.12 - 0.15)**	**0.29 (0.28 - 0.31)**	**0.08 (0.07 - 0.10)**	**0.04 (0.02 - 0.05)**	**0.10 (0.09 - 0.12)**	**0.24 (0.22 - 0.26)**	**0.16 (0.14 - 0.18)**
Wave	Household Composition	Marital Status	Highest Qualification	Housing Tenure	Household Composition	Marital Status	Highest Qualification	Housing Tenure
3	**0.08 (0.07 - 0.09)**	**0.11 (0.11 - 0.12)**	**0.05 (0.04 - 0.06)**	**0.10 (0.09 - 0.11)**	**0.10 (0.09 - 0.11)**	**0.07 (0.06 - 0.08)**	**0.04 (0.03 - 0.06)**	**0.05 (0.04 - 0.06)**
4	**0.10 (0.09 - 0.11)**	**0.14 (0.13 - 0.14)**	**0.08 (0.07 - 0.09)**	**0.13 (0.12 - 0.13)**	**0.13 (0.12 - 0.14)**	**0.09 (0.07 - 0.10)**	**0.05 (0.04 - 0.06)**	**0.07 (0.05 - 0.08)**
5	**0.11 (0.10 - 0.12)**	**0.15 (0.14 - 0.16)**	**0.10 (0.09 - 0.11)**	**0.14 (0.13 - 0.15)**	**0.16 (0.14 - 0.17)**	**0.10 (0.09 - 0.11)**	**0.06 (0.05 - 0.07)**	**0.08 (0.07 - 0.10)**
6	**0.12 (0.11 - 0.14)**	**0.17 (0.16 - 0.18)**	**0.13 (0.12 - 0.14)**	**0.16 (0.15 - 0.17)**	**0.19 (0.17 - 0.20)**	**0.12 (0.10 - 0.13)**	**0.06 (0.04 - 0.07)**	**0.10 (0.08 - 0.11)**
7	**0.13 (0.12 - 0.15)**	**0.18 (0.17 - 0.19)**	**0.15 (0.14 - 0.16)**	**0.18 (0.17 - 0.19)**	**0.21 (0.19 - 0.23)**	**0.13 (0.12 - 0.15)**	**0.07 (0.06 - 0.09)**	**0.11 (0.10 - 0.13)**
8	**0.14 (0.13 - 0.16)**	**0.20 (0.19 - 0.21)**	**0.17 (0.16 - 0.18)**	**0.19 (0.18 - 0.20)**	**0.21 (0.20 - 0.23)**	**0.13 (0.12 - 0.15)**	**0.07 (0.06 - 0.09)**	**0.13 (0.11 - 0.14)**
9	**0.15 (0.14 - 0.17)**	**0.21 (0.20 - 0.22)**	**0.18 (0.17 - 0.20)**	**0.21 (0.20 - 0.23)**	**0.21 (0.20 - 0.23)**	**0.14 (0.12 - 0.15)**	**0.08 (0.07 - 0.10)**	**0.14 (0.12 - 0.15)**

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Table B9: Partial Unconditional Coefficients of Variation (CV_c) for the UKHLS main and COVID-19 datasets, longitudinal

	Longitudinal CV_c							
	MAIN				COVID			
Wave	Sex	Ethnicity	Age	Employment Status	Sex	Ethnicity	Age	Employment Status
3	**0.02 (0.02 - 0.03)**	**0.05 (0.04 - 0.06)**	**0.07 (0.06 - 0.07)**	**0.01 (0.00 - 0.02)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.06 (0.05 - 0.07)**	**0.03 (0.01 - 0.04)**
4	**0.03 (0.02 - 0.04)**	**0.06 (0.05 - 0.07)**	**0.08 (0.07 - 0.09)**	**0.01 (0.00 - 0.02)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.08 (0.07 - 0.09)**	**0.02 (0.01 - 0.03)**
5	**0.03 (0.02 - 0.04)**	**0.07 (0.06 - 0.08)**	**0.10 (0.09 - 0.11)**	**0.01 (0.00 - 0.02)**	**0.03 (0.02 - 0.05)**	**0.03 (0.02 - 0.05)**	**0.09 (0.08 - 0.10)**	**0.02 (0.01 - 0.03)**
6	**0.04 (0.03 - 0.05)**	**0.08 (0.07 - 0.09)**	**0.12 (0.11 - 0.13)**	*0.01 (-0.00 - 0.02)*	**0.04 (0.02 - 0.05)**	**0.04 (0.02 - 0.05)**	**0.10 (0.09 - 0.12)**	**0.02 (0.01 - 0.04)**
7	**0.04 (0.03 - 0.05)**	**0.09 (0.07 - 0.10)**	**0.13 (0.12 - 0.14)**	**0.01 (0.00 - 0.02)**	**0.04 (0.02 - 0.06)**	**0.04 (0.02 - 0.05)**	**0.11 (0.09 - 0.13)**	**0.03 (0.01 - 0.04)**
8	**0.05 (0.03 - 0.06)**	**0.09 (0.08 - 0.10)**	**0.14 (0.13 - 0.15)**	*0.01 (-0.00 - 0.02*)	**0.04 (0.02 - 0.06)**	**0.04 (0.03 - 0.06)**	**0.11 (0.09 - 0.12)**	**0.03 (0.01 - 0.05)**
9	**0.05 (0.04 - 0.07)**	**0.10 (0.08 - 0.11)**	**0.16 (0.14 - 0.17)**	**0.02 (0.00 - 0.03)**	**0.05 (0.03 - 0.07)**	**0.05 (0.03 - 0.07)**	**0.11 (0.09 - 0.13)**	**0.03 (0.01 - 0.05)**
Wave	Household Composition	Marital Status	Highest Qualification	Housing Tenure	Household Composition	Marital Status	Highest Qualification	Housing Tenure
3	**0.04 (0.04 - 0.05)**	**0.02 (0.01 - 0.02)**	**0.05 (0.04 - 0.06)**	**0.05 (0.04 - 0.06)**	**0.04 (0.03 - 0.05)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.01 (0.00 - 0.02)**
4	**0.05 (0.04 - 0.06)**	**0.02 (0.01 - 0.03)**	**0.07 (0.06 - 0.08)**	**0.06 (0.06 - 0.07)**	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.05)**	**0.05 (0.03 - 0.06)**	**0.02 (0.01 - 0.03)**
5	**0.05 (0.04 - 0.06)**	**0.02 (0.01 - 0.03)**	**0.09 (0.08 - 0.09)**	**0.07 (0.06 - 0.08)**	**0.07 (0.05 - 0.08)**	**0.03 (0.02 - 0.04)**	**0.06 (0.05 - 0.08)**	**0.03 (0.02 - 0.04)**
6	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.04)**	**0.11 (0.10 - 0.12)**	**0.08 (0.07 - 0.09)**	**0.08 (0.06 - 0.09)**	**0.04 (0.02 - 0.05)**	**0.07 (0.05 - 0.08)**	**0.03 (0.02 - 0.05)**
7	**0.06 (0.04 - 0.07)**	**0.03 (0.02 - 0.04)**	**0.13 (0.12 - 0.14)**	**0.09 (0.08 - 0.10)**	**0.08 (0.07 - 0.10)**	**0.03 (0.02 - 0.05)**	**0.08 (0.06 - 0.09)**	**0.04 (0.02 - 0.06)**
8	**0.06 (0.05 - 0.08)**	**0.04 (0.02 - 0.05)**	**0.14 (0.13 - 0.15)**	**0.10 (0.08 - 0.11)**	**0.09 (0.07 - 0.11)**	**0.03 (0.01 - 0.04)**	**0.07 (0.06 - 0.09)**	**0.05 (0.03 - 0.07)**
9	**0.07 (0.05 - 0.08)**	**0.04 (0.03 - 0.05)**	**0.15 (0.13 - 0.16)**	**0.11 (0.10 - 0.12)**	**0.09 (0.07 - 0.11)**	**0.03 (0.01 - 0.05)**	**0.08 (0.06 - 0.09)**	**0.06 (0.04 - 0.08)**

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Table B10: Partial (by category) Unconditional Coefficients of Variation (CV_u) for the UKHLS main and COVID-19 datasets, longitudinal

Longitudinal CV_u (by category)

	MAIN				COVID			
Wave	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes
3	**-0.02 (-0.03 - -0.02)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**-0.07 (-0.08 - -0.07)**	**-0.02 (-0.03 - -0.00)**	**0.02 (0.00 - 0.03)**	**0.01 (0.01 - 0.02)**	**-0.05 (-0.07 - -0.02)**
4	**-0.03 (-0.03 - -0.02)**	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.03)**	**-0.09 (-0.09 - -0.08)**	*-0.01 (-0.03 - 0.00)*	*0.01 (-0.00 - 0.03)*	**0.02 (0.01 - 0.02)**	**-0.06 (-0.08 - -0.04)**
5	**-0.03 (-0.03 - -0.02)**	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.03)**	**-0.10 (-0.11 - -0.10)**	**-0.02 (-0.03 - -0.00)**	**0.02 (0.00 - 0.03)**	**0.02 (0.02 - 0.03)**	**-0.07 (-0.10 - -0.05)**
6	**-0.03 (-0.03 - -0.02)**	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**-0.11 (-0.11 - -0.10)**	*-0.02 (-0.03 - 0.00)*	*0.02 (-0.00 - 0.03)*	**0.02 (0.02 - 0.03)**	**-0.08 (-0.10 - -0.06)**
7	**-0.03 (-0.03 - -0.02)**	**0.03 (0.02 - 0.03)**	**0.04 (0.04 - 0.04)**	**-0.12 (-0.12 - -0.11)**	**-0.02 (-0.03 - -0.00)**	**0.02 (0.00 - 0.03)**	**0.03 (0.02 - 0.03)**	**-0.09 (-0.11 - -0.07)**
8	**-0.03 (-0.03 - -0.02)**	**0.03 (0.02 - 0.03)**	**0.04 (0.04 - 0.04)**	**-0.12 (-0.12 - -0.11)**	**-0.02 (-0.03 - -0.00)**	**0.02 (0.00 - 0.03)**	**0.03 (0.02 - 0.03)**	**-0.10 (-0.12 - -0.08)**
9	**-0.03 (-0.04 - -0.02)**	**0.03 (0.02 - 0.04)**	**0.04 (0.04 - 0.04)**	**-0.13 (-0.13 - -0.12)**	**-0.02 (-0.04 - -0.01)**	**0.02 (0.01 - 0.04)**	**0.03 (0.02 - 0.03)**	**-0.10 (-0.12 - -0.08)**
Wave	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44
3	**-0.07 (-0.07 - -0.06)**	**-0.09 (-0.09 - -0.08)**	**-0.03 (-0.04 - -0.03)**	**0.01 (0.00 - 0.02)**	**-0.06 (-0.08 - -0.04)**	**-0.05 (-0.08 - -0.03)**	**-0.03 (-0.05 - -0.01)**	*-0.01 (-0.03 - 0.01)*
4	**-0.09 (-0.09 - -0.08)**	**-0.10 (-0.11 - -0.09)**	**-0.04 (-0.05 - -0.03)**	**0.02 (0.01 - 0.03)**	**-0.08 (-0.10 - -0.07)**	**-0.06 (-0.09 - -0.04)**	**-0.05 (-0.07 - -0.03)**	**-0.02 (-0.04 - -0.00)**
5	**-0.10 (-0.11 - -0.10)**	**-0.11 (-0.12 - -0.11)**	**-0.05 (-0.05 - -0.04)**	**0.03 (0.02 - 0.04)**	**-0.10 (-0.11 - -0.08)**	**-0.08 (-0.10 - -0.06)**	**-0.05 (-0.07 - -0.03)**	**-0.03 (-0.05 - -0.01)**
6	**-0.12 (-0.13 - -0.12)**	**-0.12 (-0.13 - -0.11)**	**-0.05 (-0.06 - -0.05)**	**0.03 (0.02 - 0.04)**	**-0.11 (-0.12 - -0.09)**	**-0.10 (-0.12 - -0.08)**	**-0.07 (-0.09 - -0.05)**	**-0.04 (-0.06 - -0.02)**
7	**-0.14 (-0.14 - -0.13)**	**-0.13 (-0.13 - -0.12)**	**-0.05 (-0.06 - -0.05)**	**0.03 (0.02 - 0.04)**	**-0.11 (-0.13 - -0.10)**	**-0.10 (-0.12 - -0.09)**	**-0.08 (-0.10 - -0.06)**	**-0.05 (-0.07 - -0.03)**
8	**-0.14 (-0.15 - -0.14)**	**-0.13 (-0.14 - -0.12)**	**-0.05 (-0.06 - -0.04)**	**0.03 (0.02 - 0.04)**	**-0.11 (-0.13 - -0.10)**	**-0.10 (-0.12 - -0.09)**	**-0.08 (-0.10 - -0.06)**	**-0.06 (-0.07 - -0.04)**
9	**-0.16 (-0.16 - -0.15)**	**-0.13 (-0.14 - -0.12)**	**-0.06 (-0.06 - -0.05)**	**0.03 (0.02 - 0.04)**	**-0.12 (-0.13 - -0.11)**	**-0.11 (-0.13 - -0.10)**	**-0.07 (-0.09 - -0.06)**	**-0.05 (-0.06 - -0.03)**
Wave	Age: 45-54	Age: 55-64	Age: 65+		Age: 45-54	Age: 55-64	Age: 65+	
3	**0.04 (0.03 - 0.05)**	**0.06 (0.05 - 0.07)**	**0.03 (0.02 - 0.03)**		*0.01 (-0.01 - 0.03)*	**0.05 (0.03 - 0.07)**	**0.04 (0.02 - 0.07)**	
4	**0.05 (0.04 - 0.06)**	**0.08 (0.07 - 0.09)**	**0.02 (0.01 - 0.03)**		*0.01 (-0.01 - 0.03)*	**0.06 (0.04 - 0.09)**	**0.06 (0.03 - 0.08)**	
5	**0.06 (0.05 - 0.07)**	**0.10 (0.09 - 0.11)**	**0.01 (0.00 - 0.02)**		*0.01 (-0.01 - 0.03)*	**0.08 (0.06 - 0.11)**	**0.07 (0.05 - 0.10)**	
6	**0.07 (0.06 - 0.08)**	**0.12 (0.10 - 0.13)**	*0.00 (-0.00 - 0.01)*		*0.01 (-0.01 - 0.03)*	**0.10 (0.08 - 0.12)**	**0.09 (0.07 - 0.12)**	
7	**0.08 (0.07 - 0.09)**	**0.13 (0.12 - 0.14)**	**-0.01 (-0.02 - -0.00)**		*0.01 (-0.01 - 0.03)*	**0.11 (0.08 - 0.13)**	**0.11 (0.08 - 0.13)**	
8	**0.09 (0.08 - 0.10)**	**0.15 (0.14 - 0.16)**	**-0.03 (-0.04 - -0.02)**		*0.02 (-0.00 - 0.04)*	**0.11 (0.09 - 0.14)**	**0.10 (0.08 - 0.13)**	
9	**0.10 (0.09 - 0.11)**	**0.17 (0.16 - 0.19)**	**-0.04 (-0.05 - -0.04)**		**0.02 (0.00 - 0.04)**	**0.11 (0.09 - 0.14)**	**0.09 (0.07 - 0.12)**	

Table B10 continued on the next page.

Table B10 cont.

Wave	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other
3	**-0.01 (-0.02 - -0.01)**	**-0.04 (-0.05 - -0.03)**	**0.04 (0.03 - 0.05)**	*-0.00 (-0.01 - 0.01)*	*-0.01 (-0.03 - 0.00)*	**-0.03 (-0.06 - -0.01)**	**0.05 (0.03 - 0.07)**	*-0.02 (-0.05 - 0.01)*
4	**-0.01 (-0.01 - -0.00)**	**-0.05 (-0.05 - -0.04)**	**0.04 (0.03 - 0.05)**	**-0.01 (-0.02 - -0.00)**	**-0.02 (-0.04 - -0.01)**	**-0.04 (-0.06 - -0.01)**	**0.07 (0.05 - 0.09)**	*-0.02 (-0.05 - 0.01)*
5	*-0.00 (-0.01 - 0.00)*	**-0.05 (-0.06 - -0.04)**	**0.04 (0.03 - 0.05)**	**-0.01 (-0.02 - -0.01)**	**-0.03 (-0.05 - -0.02)**	**-0.03 (-0.06 - -0.01)**	**0.08 (0.06 - 0.11)**	*-0.02 (-0.05 - 0.00)*
6	*0.00 (-0.00 - 0.01)*	**-0.06 (-0.06 - -0.05)**	**0.04 (0.03 - 0.04)**	**-0.02 (-0.03 - -0.01)**	**-0.05 (-0.06 - -0.03)**	**-0.03 (-0.06 - -0.00)**	**0.11 (0.08 - 0.13)**	*-0.02 (-0.05 - 0.01)*
7	**0.01 (0.01 - 0.02)**	**-0.06 (-0.07 - -0.05)**	**0.03 (0.02 - 0.04)**	**-0.02 (-0.03 - -0.02)**	**-0.06 (-0.07 - -0.04)**	*-0.03 (-0.06 - 0.00)*	**0.13 (0.10 - 0.15)**	**-0.03 (-0.06 - -0.00)**
8	**0.02 (0.02 - 0.03)**	**-0.06 (-0.07 - -0.06)**	**0.01 (0.01 - 0.02)**	**-0.03 (-0.03 - -0.02)**	**-0.05 (-0.07 - -0.04)**	**-0.03 (-0.06 - -0.00)**	**0.13 (0.10 - 0.15)**	**-0.04 (-0.06 - -0.01)**
9	**0.03 (0.03 - 0.04)**	**-0.07 (-0.08 - -0.06)**	*0.00 (-0.00 - 0.01)*	**-0.03 (-0.04 - -0.02)**	**-0.05 (-0.06 - -0.04)**	*-0.03 (-0.05 - 0.00)*	**0.12 (0.10 - 0.15)**	**-0.04 (-0.07 - -0.02)**

Wave	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children
3	*0.01 (-0.00 - 0.02)*	*-0.00 (-0.01 - 0.01)*	**0.04 (0.04 - 0.05)**	**0.02 (0.01 - 0.03)**	*0.01 (-0.02 - 0.03)*	*-0.02 (-0.05 - 0.00)*	**0.07 (0.05 - 0.09)**	*-0.02 (-0.04 - 0.00)*
4	**0.01 (0.00 - 0.02)**	**-0.01 (-0.02 - -0.00)**	**0.06 (0.05 - 0.06)**	**0.02 (0.01 - 0.03)**	*0.01 (-0.01 - 0.04)*	**-0.03 (-0.05 - -0.01)**	**0.09 (0.07 - 0.10)**	**-0.03 (-0.05 - -0.01)**
5	**0.01 (0.01 - 0.02)**	**-0.01 (-0.02 - -0.01)**	**0.07 (0.06 - 0.07)**	**0.02 (0.01 - 0.03)**	*0.02 (-0.01 - 0.04)*	**-0.04 (-0.06 - -0.02)**	**0.11 (0.09 - 0.13)**	**-0.05 (-0.07 - -0.03)**
6	**0.02 (0.01 - 0.03)**	**-0.03 (-0.03 - -0.02)**	**0.07 (0.07 - 0.08)**	**0.02 (0.01 - 0.03)**	*0.02 (-0.01 - 0.05)*	**-0.06 (-0.08 - -0.04)**	**0.13 (0.11 - 0.15)**	**-0.07 (-0.09 - -0.06)**
7	**0.02 (0.01 - 0.03)**	**-0.03 (-0.04 - -0.02)**	**0.08 (0.08 - 0.09)**	**0.01 (0.00 - 0.02)**	**0.03 (0.01 - 0.06)**	**-0.06 (-0.08 - -0.05)**	**0.15 (0.13 - 0.17)**	**-0.09 (-0.11 - -0.07)**
8	**0.01 (0.00 - 0.02)**	**-0.04 (-0.04 - -0.03)**	**0.10 (0.09 - 0.10)**	**0.01 (0.00 - 0.02)**	**0.03 (0.00 - 0.05)**	**-0.07 (-0.09 - -0.05)**	**0.15 (0.13 - 0.17)**	**-0.10 (-0.11 - -0.08)**
9	*0.01 (-0.00 - 0.02)*	**-0.04 (-0.05 - -0.04)**	**0.10 (0.09 - 0.11)**	*0.01 (-0.00 - 0.01)*	**0.03 (0.00 - 0.05)**	**-0.07 (-0.08 - -0.05)**	**0.15 (0.13 - 0.16)**	**-0.09 (-0.10 - -0.07)**

Wave	HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children			HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children		
3	**-0.05 (-0.06 - -0.05)**	**-0.04 (-0.05 - -0.03)**			**-0.03 (-0.05 - -0.01)**	**-0.04 (-0.06 - -0.02)**		
4	**-0.06 (-0.07 - -0.06)**	**-0.05 (-0.06 - -0.04)**			**-0.03 (-0.05 - -0.01)**	**-0.06 (-0.08 - -0.04)**		
5	**-0.07 (-0.07 - -0.06)**	**-0.06 (-0.07 - -0.05)**			**-0.04 (-0.06 - -0.01)**	**-0.06 (-0.08 - -0.04)**		
6	**-0.07 (-0.07 - -0.06)**	**-0.07 (-0.08 - -0.06)**			**-0.03 (-0.06 - -0.01)**	**-0.06 (-0.08 - -0.04)**		
7	**-0.06 (-0.07 - -0.06)**	**-0.07 (-0.08 - -0.07)**			**-0.04 (-0.06 - -0.02)**	**-0.06 (-0.08 - -0.04)**		
8	**-0.06 (-0.07 - -0.06)**	**-0.08 (-0.09 - -0.07)**			**-0.03 (-0.06 - -0.01)**	**-0.06 (-0.08 - -0.04)**		
9	**-0.06 (-0.07 - -0.05)**	**-0.08 (-0.09 - -0.08)**			**-0.04 (-0.06 - -0.02)**	**-0.06 (-0.08 - -0.04)**		

Table B10 continued on the next page.

Table B10 cont.

Wave	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed
3	**-0.09 (-0.10 - -0.09)**	**0.06 (0.05 - 0.06)**	**0.03 (0.02 - 0.04)**	*0.01 (-0.00 - 0.02)*	**-0.05 (-0.07 - -0.04)**	**0.04 (0.03 - 0.06)**	*0.01 (-0.01 - 0.04)*	*-0.02 (-0.05 - 0.01)*
4	**-0.11 (-0.12 - -0.10)**	**0.07 (0.07 - 0.08)**	**0.04 (0.03 - 0.05)**	*0.00 (-0.01 - 0.01)*	**-0.07 (-0.09 - -0.05)**	**0.05 (0.04 - 0.07)**	*0.02 (-0.01 - 0.04)*	*-0.02 (-0.05 - 0.01)*
5	**-0.12 (-0.13 - -0.12)**	**0.08 (0.07 - 0.09)**	**0.05 (0.04 - 0.05)**	*-0.00 (-0.01 - 0.00)*	**-0.09 (-0.10 - -0.07)**	**0.06 (0.04 - 0.07)**	*0.03 (-0.00 - 0.05)*	*-0.01 (-0.04 - 0.02)*
6	**-0.14 (-0.14 - -0.13)**	**0.09 (0.09 - 0.10)**	**0.05 (0.04 - 0.06)**	**-0.01 (-0.02 - -0.01)**	**-0.10 (-0.12 - -0.08)**	**0.07 (0.05 - 0.08)**	**0.03 (0.00 - 0.05)**	*-0.00 (-0.03 - 0.03)*
7	**-0.14 (-0.15 - -0.14)**	**0.10 (0.09 - 0.11)**	**0.05 (0.05 - 0.06)**	**-0.02 (-0.03 - -0.02)**	**-0.11 (-0.13 - -0.09)**	**0.08 (0.06 - 0.09)**	*0.03 (-0.00 - 0.05)*	*0.00 (-0.03 - 0.03)*
8	**-0.15 (-0.16 - -0.14)**	**0.11 (0.11 - 0.12)**	**0.06 (0.05 - 0.07)**	**-0.04 (-0.05 - -0.03)**	**-0.11 (-0.13 - -0.10)**	**0.08 (0.06 - 0.09)**	*0.02 (-0.00 - 0.05)*	*0.01 (-0.03 - 0.04)*
9	**-0.16 (-0.16 - -0.15)**	**0.12 (0.12 - 0.13)**	**0.06 (0.05 - 0.07)**	**-0.05 (-0.06 - -0.04)**	**-0.12 (-0.13 - -0.10)**	**0.08 (0.06 - 0.09)**	*0.02 (-0.00 - 0.05)*	*0.00 (-0.03 - 0.03)*

Wave	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE
3	**-0.03 (-0.03 - -0.02)**	**0.04 (0.03 - 0.04)**	**-0.02 (-0.02 - -0.01)**	**-0.01 (-0.02 - -0.00)**	*-0.02 (-0.06 - 0.01)*	***0.03 (0.01 - 0.04)***	*-0.00 (-0.02 - 0.02)*	*-0.01 (-0.03 - 0.02)*
4	**-0.05 (-0.05 - -0.04)**	**0.06 (0.05 - 0.07)**	**-0.02 (-0.03 - -0.01)**	**-0.02 (-0.02 - -0.01)**	*-0.03 (-0.06 - 0.01)*	***0.03 (0.01 - 0.05)***	*-0.01 (-0.03 - 0.01)*	*-0.01 (-0.03 - 0.01)*
5	**-0.06 (-0.06 - -0.05)**	**0.07 (0.06 - 0.08)**	**-0.02 (-0.03 - -0.01)**	**-0.02 (-0.03 - -0.01)**	*-0.02 (-0.06 - 0.01)*	***0.04 (0.02 - 0.06)***	*-0.01 (-0.03 - 0.01)*	*-0.01 (-0.04 - 0.01)*
6	**-0.07 (-0.08 - -0.07)**	**0.10 (0.09 - 0.10)**	**-0.03 (-0.04 - -0.02)**	**-0.03 (-0.03 - -0.02)**	*-0.02 (-0.06 - 0.01)*	***0.04 (0.02 - 0.06)***	*-0.02 (-0.04 - 0.00)*	*-0.01 (-0.03 - 0.01)*
7	**-0.09 (-0.09 - -0.08)**	**0.11 (0.11 - 0.12)**	**-0.03 (-0.04 - -0.02)**	**-0.03 (-0.03 - -0.02)**	*-0.02 (-0.05 - 0.02)*	***0.04 (0.03 - 0.06)***	*-0.02 (-0.04 - 0.00)*	*-0.01 (-0.03 - 0.01)*
8	**-0.10 (-0.11 - -0.09)**	**0.13 (0.12 - 0.14)**	**-0.03 (-0.04 - -0.02)**	**-0.03 (-0.04 - -0.02)**	*-0.02 (-0.06 - 0.01)*	***0.05 (0.03 - 0.06)***	**-0.02 (-0.04 - -0.00)**	*-0.01 (-0.03 - 0.01)*
9	**-0.11 (-0.12 - -0.11)**	**0.14 (0.13 - 0.15)**	**-0.03 (-0.04 - -0.02)**	**-0.03 (-0.04 - -0.02)**	**-0.04 (-0.07 - -0.01)**	***0.06 (0.04 - 0.07)***	**-0.03 (-0.05 - -0.01)**	*-0.01 (-0.03 - 0.01)*

Wave	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other
3	*0.00 (-0.00 - 0.01)*	**0.05 (0.05 - 0.06)**	**-0.08 (-0.09 - -0.07)**	**-0.01 (-0.02 - -0.00)**	*-0.02 (-0.05 - 0.01)*	**0.03 (0.01 - 0.04)**	**-0.04 (-0.06 - -0.02)**	*-0.00 (-0.02 - 0.01)*
4	*0.00 (-0.00 - 0.01)*	**0.07 (0.06 - 0.07)**	**-0.10 (-0.11 - -0.10)**	*-0.01 (-0.01 - 0.00)*	*-0.02 (-0.05 - 0.01)*	**0.04 (0.02 - 0.05)**	**-0.06 (-0.08 - -0.03)**	*-0.00 (-0.02 - 0.01)*
5	*0.00 (-0.01 - 0.01)*	**0.08 (0.07 - 0.08)**	**-0.12 (-0.12 - -0.11)**	**-0.01 (-0.02 - -0.00)**	**-0.03 (-0.06 - -0.00)**	**0.05 (0.03 - 0.06)**	**-0.07 (-0.09 - -0.05)**	*0.00 (-0.02 - 0.02)*
6	*-0.00 (-0.01 - 0.01)*	**0.09 (0.08 - 0.09)**	**-0.13 (-0.14 - -0.13)**	**-0.01 (-0.02 - -0.00)**	**-0.03 (-0.06 - -0.00)**	**0.05 (0.04 - 0.07)**	**-0.08 (-0.11 - -0.06)**	*0.00 (-0.02 - 0.02)*
7	**-0.01 (-0.02 - -0.00)**	**0.10 (0.09 - 0.10)**	**-0.15 (-0.15 - -0.14)**	**-0.02 (-0.02 - -0.01)**	**-0.04 (-0.06 - -0.01)**	**0.06 (0.05 - 0.08)**	**-0.10 (-0.12 - -0.08)**	*0.00 (-0.02 - 0.02)*
8	**-0.01 (-0.02 - -0.00)**	**0.11 (0.10 - 0.11)**	**-0.16 (-0.16 - -0.15)**	**-0.02 (-0.03 - -0.01)**	**-0.03 (-0.06 - -0.01)**	**0.07 (0.06 - 0.08)**	**-0.11 (-0.13 - -0.09)**	*0.00 (-0.02 - 0.02)*
9	**-0.02 (-0.03 - -0.01)**	**0.12 (0.11 - 0.12)**	**-0.18 (-0.18 - -0.17)**	**-0.02 (-0.02 - -0.01)**	**-0.03 (-0.06 - -0.01)**	**0.08 (0.07 - 0.09)**	**-0.12 (-0.14 - -0.10)**	*-0.01 (-0.02 - 0.01)*

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.

Abbrev.: Employment Status – Emp Stat; Employed, In Education or Training – Emp, In Educ or Training; Household Composition – HH Comp; Marital Status – Mar Stat; Highest Qualification – High Qual; Housing Tenure – Tenure

Table B11: Partial (by category) Conditional Coefficients of Variation (CV_c) for the UKHLS main and COVID-19 datasets, longitudinal

Longitudinal CVc (by category)

	MAIN				COVID			
Wave	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes	Sex: Male	Sex: Female	Ethnicity: No	Ethnicity: Yes
3	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.05 (0.04 - 0.05)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.03)**
4	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.06 (0.05 - 0.06)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.03 (0.02 - 0.04)**
5	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.03 (0.03 - 0.03)**	**0.07 (0.06 - 0.07)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.03 (0.02 - 0.04)**
6	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.07 (0.06 - 0.08)**	**0.02 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.04 (0.02 - 0.05)**
7	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.03 (0.03 - 0.04)**	**0.08 (0.07 - 0.09)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.04 (0.03 - 0.05)**
8	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.08 (0.07 - 0.09)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.02 (0.02 - 0.03)**	**0.04 (0.03 - 0.06)**
9	**0.04 (0.03 - 0.05)**	**0.04 (0.03 - 0.05)**	**0.04 (0.03 - 0.04)**	**0.09 (0.08 - 0.10)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.05)**	**0.02 (0.02 - 0.03)**	**0.05 (0.03 - 0.06)**

Wave	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44	Age: 16-19	Age: 20-24	Age: 25-34	Age: 35-44
3	**0.02 (0.01 - 0.02)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**
4	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.03 (0.03 - 0.04)**	**0.03 (0.03 - 0.03)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.02 (0.02 - 0.03)**
5	**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.04)**	**0.04 (0.04 - 0.05)**	**0.04 (0.03 - 0.04)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.03 (0.02 - 0.03)**
6	**0.04 (0.03 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.05 (0.05 - 0.06)**	**0.04 (0.04 - 0.05)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.04 (0.04 - 0.05)**	**0.03 (0.03 - 0.04)**
7	**0.04 (0.04 - 0.05)**	**0.04 (0.04 - 0.05)**	**0.05 (0.05 - 0.06)**	**0.05 (0.04 - 0.05)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.05 (0.04 - 0.06)**	**0.04 (0.03 - 0.04)**
8	**0.04 (0.04 - 0.05)**	**0.04 (0.04 - 0.05)**	**0.06 (0.05 - 0.06)**	**0.05 (0.04 - 0.05)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.05 (0.04 - 0.06)**	**0.03 (0.03 - 0.04)**
9	**0.05 (0.04 - 0.05)**	**0.04 (0.04 - 0.05)**	**0.06 (0.05 - 0.07)**	**0.05 (0.04 - 0.05)**	**0.03 (0.02 - 0.04)**	**0.05 (0.03 - 0.06)**	**0.05 (0.04 - 0.06)**	**0.04 (0.03 - 0.04)**

Wave	Age: 45-54	Age: 55-64	Age: 65+		Age: 45-54	Age: 55-64	Age: 65+	
3	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.01 (0.01 - 0.01)**		**0.02 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	
4	**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.02)**		**0.03 (0.03 - 0.04)**	**0.03 (0.03 - 0.04)**	**0.01 (0.00 - 0.01)**	
5	**0.04 (0.03 - 0.05)**	**0.05 (0.04 - 0.06)**	**0.02 (0.02 - 0.03)**		**0.04 (0.03 - 0.04)**	**0.04 (0.04 - 0.05)**	**0.01 (0.01 - 0.02)**	
6	**0.05 (0.04 - 0.05)**	**0.06 (0.05 - 0.07)**	**0.03 (0.02 - 0.03)**		**0.04 (0.04 - 0.05)**	**0.05 (0.04 - 0.06)**	**0.01 (0.01 - 0.02)**	
7	**0.05 (0.04 - 0.06)**	**0.07 (0.06 - 0.08)**	**0.03 (0.03 - 0.04)**		**0.05 (0.04 - 0.06)**	**0.05 (0.04 - 0.06)**	**0.01 (0.01 - 0.02)**	
8	**0.05 (0.04 - 0.06)**	**0.08 (0.07 - 0.09)**	**0.04 (0.04 - 0.05)**		**0.05 (0.04 - 0.06)**	**0.05 (0.04 - 0.06)**	**0.01 (0.01 - 0.02)**	
9	**0.06 (0.05 - 0.06)**	**0.10 (0.08 - 0.11)**	**0.05 (0.05 - 0.06)**		**0.05 (0.04 - 0.06)**	**0.05 (0.04 - 0.06)**	**0.01 (0.01 - 0.02)**	

Table B11 continued on the next page.

Table B11 cont.

Wave	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other	Emp Stat: Emp, In Educ or Training	Emp Stat: Unemployed	Emp Stat: Retired	Emp Stat: Other
3	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	**0.00 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	*0.00 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*
4	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	*0.00 (-0.00 - 0.01)*	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.02)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*
5	*0.01 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.00 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.02)*	*0.00 (-0.03 - 0.03)*	*0.00 (-0.01 - 0.02)*	*0.00 (-0.01 - 0.02)*
6	*0.00 (-0.00 - 0.01)*	*0.00 (-0.01 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.02)*	*0.00 (-0.01 - 0.02)*	*0.01 (-0.00 - 0.02)*	*0.00 (-0.01 - 0.02)*
7	*0.00 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.02)*	*0.00 (-0.01 - 0.01)*	*0.01 (-0.00 - 0.02)*	**0.01 (0.00 - 0.02)**	*0.01 (-0.00 - 0.02)*	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.02)*
8	*0.01 (-0.00 - 0.01)*	*0.01 (-0.01 - 0.02)*	*0.00 (-0.02 - 0.03)*	*0.01 (-0.00 - 0.02)*	**0.01 (0.00 - 0.02)**	*0.01 (-0.01 - 0.02)*	**0.01 (0.00 - 0.02)**	*0.00 (-0.01 - 0.02)*
9	*0.01 (-0.00 - 0.02)*	*0.01 (-0.00 - 0.02)*	*0.00 (-0.01 - 0.02)*	*0.01 (-0.00 - 0.02)*	**0.02 (0.01 - 0.03)**	*0.01 (-0.00 - 0.03)*	**0.02 (0.00 - 0.03)**	*0.01 (-0.00 - 0.02)*

Wave	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children	HH Comp: 1 adult, no children	HH Comp: 1 adult, children	HH Comp: couple, no children	HH Comp: couple, children
3	**0.01 (0.01 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.01)*	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**
4	**0.01 (0.01 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.01)**	*0.01 (-0.00 - 0.02)*	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.01)**
5	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.02)**
6	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.05 (0.04 - 0.06)**	**0.03 (0.02 - 0.04)**
7	**0.02 (0.01 - 0.03)**	*0.01 (-0.00 - 0.01)*	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	**0.06 (0.05 - 0.07)**	**0.04 (0.03 - 0.05)**
8	**0.03 (0.02 - 0.03)**	*0.01 (-0.00 - 0.01)*	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.02)**	**0.03 (0.01 - 0.04)**	**0.06 (0.05 - 0.07)**	**0.05 (0.04 - 0.06)**
9	**0.03 (0.02 - 0.04)**	*0.01 (-0.00 - 0.01)*	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.03 (0.01 - 0.04)**	**0.06 (0.05 - 0.07)**	**0.04 (0.03 - 0.06)**

Wave	HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children			HH Comp: 2+ adults, no children	HH Comp: 2+ adults, children		
3	**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**			**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**		
4	**0.04 (0.03 - 0.04)**	**0.01 (0.01 - 0.02)**			**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**		
5	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.02)**			**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.02)**		
6	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.03)**			**0.02 (0.02 - 0.03)**	**0.01 (0.01 - 0.02)**		
7	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.03)**			**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**		
8	**0.04 (0.03 - 0.05)**	**0.03 (0.02 - 0.04)**			**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.02)**		
9	**0.04 (0.03 - 0.05)**	**0.03 (0.02 - 0.04)**			**0.03 (0.02 - 0.04)**	**0.01 (0.01 - 0.02)**		

Table B11 continued on the next page.

Table B11 cont.

Wave	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed	Mar Stat: Single	Mar Stat: Married	Mar Stat: Separated/Divorced	Mar Stat: Widowed
3	**0.01 (0.00 - 0.01)**	**0.00 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.00 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.03)**
4	**0.01 (0.00 - 0.02)**	**0.00 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**
5	**0.01 (0.00 - 0.02)**	**0.00 (0.00 - 0.01)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**
6	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**
7	**0.01 (0.01 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.01 (0.00 - 0.02)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	**0.02 (0.01 - 0.03)**
8	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	*0.01 (-0.00 - 0.02)*	*0.01 (-0.00 - 0.01)*	**0.01 (0.00 - 0.02)**	**0.02 (0.00 - 0.03)**
9	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.03)**	*0.01 (-0.00 - 0.02)*	*0.01 (-0.00 - 0.01)*	*0.01 (-0.00 - 0.02)*	**0.02 (0.00 - 0.03)**

Wave	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE	High Qual: None	High Qual: Degree	High Qual: A-Level	High Qual: GCSE
3	**0.04 (0.03 - 0.04)**	**0.03 (0.02 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.01 (0.01 - 0.01)**
4	**0.05 (0.04 - 0.06)**	**0.04 (0.04 - 0.05)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	**0.01 (0.01 - 0.02)**
5	**0.06 (0.05 - 0.06)**	**0.05 (0.05 - 0.06)**	**0.02 (0.02 - 0.02)**	**0.02 (0.02 - 0.02)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.02 (0.01 - 0.02)**
6	**0.07 (0.06 - 0.08)**	**0.07 (0.06 - 0.08)**	**0.02 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.02)**
7	**0.08 (0.07 - 0.09)**	**0.08 (0.07 - 0.09)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.02)**
8	**0.09 (0.08 - 0.10)**	**0.09 (0.08 - 0.10)**	**0.03 (0.02 - 0.03)**	**0.03 (0.03 - 0.03)**	**0.03 (0.02 - 0.04)**	**0.03 (0.02 - 0.04)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.02)**
9	**0.09 (0.08 - 0.10)**	**0.10 (0.09 - 0.11)**	**0.03 (0.03 - 0.03)**	**0.03 (0.03 - 0.04)**	**0.04 (0.03 - 0.06)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.03)**	**0.02 (0.01 - 0.02)**

Wave	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other	High Qual: Other	Tenure: Owned	Tenure: Rented	Tenure: Other
3	**0.02 (0.01 - 0.02)**	**0.03 (0.02 - 0.03)**	**0.04 (0.03 - 0.04)**	**0.01 (0.00 - 0.02)**	**0.02 (0.02 - 0.03)**	**0.01 (0.00 - 0.01)**	**0.01 (0.00 - 0.02)**	*0.01 (-0.01 - 0.02)*
4	**0.02 (0.01 - 0.02)**	**0.04 (0.03 - 0.04)**	**0.05 (0.04 - 0.06)**	*0.01 (-0.00 - 0.01)*	**0.03 (0.02 - 0.04)**	**0.01 (0.00 - 0.02)**	**0.01 (0.01 - 0.02)**	*0.00 (-0.01 - 0.02)*
5	**0.02 (0.02 - 0.03)**	**0.04 (0.03 - 0.04)**	**0.05 (0.05 - 0.06)**	**0.01 (0.00 - 0.02)**	**0.04 (0.03 - 0.05)**	**0.02 (0.01 - 0.02)**	**0.02 (0.01 - 0.03)**	*0.00 (-0.02 - 0.02)*
6	**0.03 (0.02 - 0.04)**	**0.04 (0.04 - 0.05)**	**0.06 (0.05 - 0.07)**	**0.01 (0.00 - 0.02)**	**0.05 (0.04 - 0.06)**	**0.02 (0.01 - 0.03)**	**0.03 (0.02 - 0.04)**	*0.00 (-0.03 - 0.03)*
7	**0.04 (0.03 - 0.05)**	**0.05 (0.04 - 0.05)**	**0.07 (0.06 - 0.08)**	**0.02 (0.01 - 0.03)**	**0.06 (0.05 - 0.07)**	**0.02 (0.02 - 0.03)**	**0.03 (0.02 - 0.04)**	*0.00 (-0.02 - 0.03)*
8	**0.04 (0.03 - 0.05)**	**0.05 (0.05 - 0.06)**	**0.08 (0.07 - 0.08)**	**0.02 (0.01 - 0.03)**	**0.05 (0.04 - 0.07)**	**0.03 (0.02 - 0.04)**	**0.04 (0.03 - 0.05)**	*0.00 (-0.02 - 0.03)*
9	**0.05 (0.04 - 0.06)**	**0.06 (0.05 - 0.07)**	**0.09 (0.08 - 0.10)**	**0.02 (0.00 - 0.03)**				

Note: 95% confidence intervals in parentheses. Boldface indicates significance. Italics indicate non-significance.
Abbrev.: Employment Status – Emp Stat; Employed, In Education or Training – Emp, In Educ or Training; Household Composition – HH Comp; Marital Status – Mar Stat; Highest Qualification – High Qual; Housing Tenure – Tenure

Appendix B: Figures

1 PRE-NOTIFICATION LETTER (April 2020 only)
[Understanding Society headed letter, including standard contact details]

Dear <Title, First name, Surname>,

Thank you for your continued help and support for *Understanding Society*.

As you know, under normal circumstances we invite you to take part in the Study once a year.

However this year, we are not living under normal circumstances. The **coronavirus pandemic** is a shock to society that perhaps has no precedent since the last world war. While it is most immediately a public health emergency, it is already clear that it will also have long-lasting social and economic consequences that will significantly impact us all in the future.

This is why we would like to use *Understanding Society* to collect new and important information. In addition to your annual interview, we would like to invite you to a series of short monthly online surveys for the next year. These surveys will be about how the coronavirus is affecting your life.

Each month that you take part, you will earn a £2 reward.

We will send the invitations to you by email and/or SMS text message, depending on what contact information we have for you. If you need to update your email or mobile number, please let us know at https://www.understandingsociety.ac.uk/participants/update

{IF emailflag = 1 AND mobnoflag = 0: We currently have this email address for you: <encrypted email>, but no mobile number.}

{IF mobnoflag = 1 AND emailflag = 0: We currently have this mobile phone number for you: <encrypted number>, but no email address.}

{IF emailflag = 1 AND mobnoflag = 1: We currently have this email address for you: <encrypted email> and this mobile phone number: <encrypted number>.}

{IF emailflag = 0 AND mobnoflag = 0: We do not have an email address or a mobile phone number for you. If you would like to take part, please update your contact details on our website using the link above.}

This survey is entirely confidential and anonymous. The research findings will not identify you. Your personal details will not be shared with anyone other than Ipsos MORI (our partner in this study).

If you do NOT want us to contact you for this monthly coronavirus survey, please contact our partners for this study, Ipsos MORI on undcorona@ipsos.com or 0800 141 3656. If you would like to take part in the study, you do not need to do anything.

With many thanks,

Professor Michaela Benzeval – Director, *Understanding Society*

Understanding Society is being conducted in accordance with the Data Protection Act. This means your personal details will be kept strictly confidential and you and your household will not be identifiable from the data. To view our privacy policy, see https://www.understandingsociety.ac.uk/participants/coronastudy

Frequently Asked Questions: *Understanding Society* Coronavirus Study

For more information about this part of the study, please see the FAQs below, or click here: https://www.understandingsociety.ac.uk/participants/coronastudy.

What is this survey about and how long will it take?

The coronavirus pandemic is a shock to society that perhaps has no precedent since the last world war. While it is most immediately a public health emergency, it is already clear that it will also have social and economic consequences that will significantly impact the welfare and wellbeing of individuals, families and communities going forward. By completing a short 20-minute survey each month, you will help researchers:

- track how the virus is impacting our lives month-by-month
- see the effect of changes in government guidelines on hygiene and social distancing on our lives
- understand the effect of the government financial support schemes
- design policies to help people deal with the effects of the coronavirus.

What do I need to do?

We will send you your first invite to the ***Understanding Society* Coronavirus Study** during April, and then at the same time each month. The only thing you need to do now is to update your contact details if they are not correct. Ipsos MORI will then contact you using those details.

What will I get if I take part?

To thank you for this extra information, we will create a 'reward account' in your name and credit you with **£2 for each month** that you answer the survey. You will be able to exchange the reward amount for a range of gift-cards and electronic vouchers at any point.

Figure B1: Understanding Society COVID-19 Study pre-notification letter April 2020

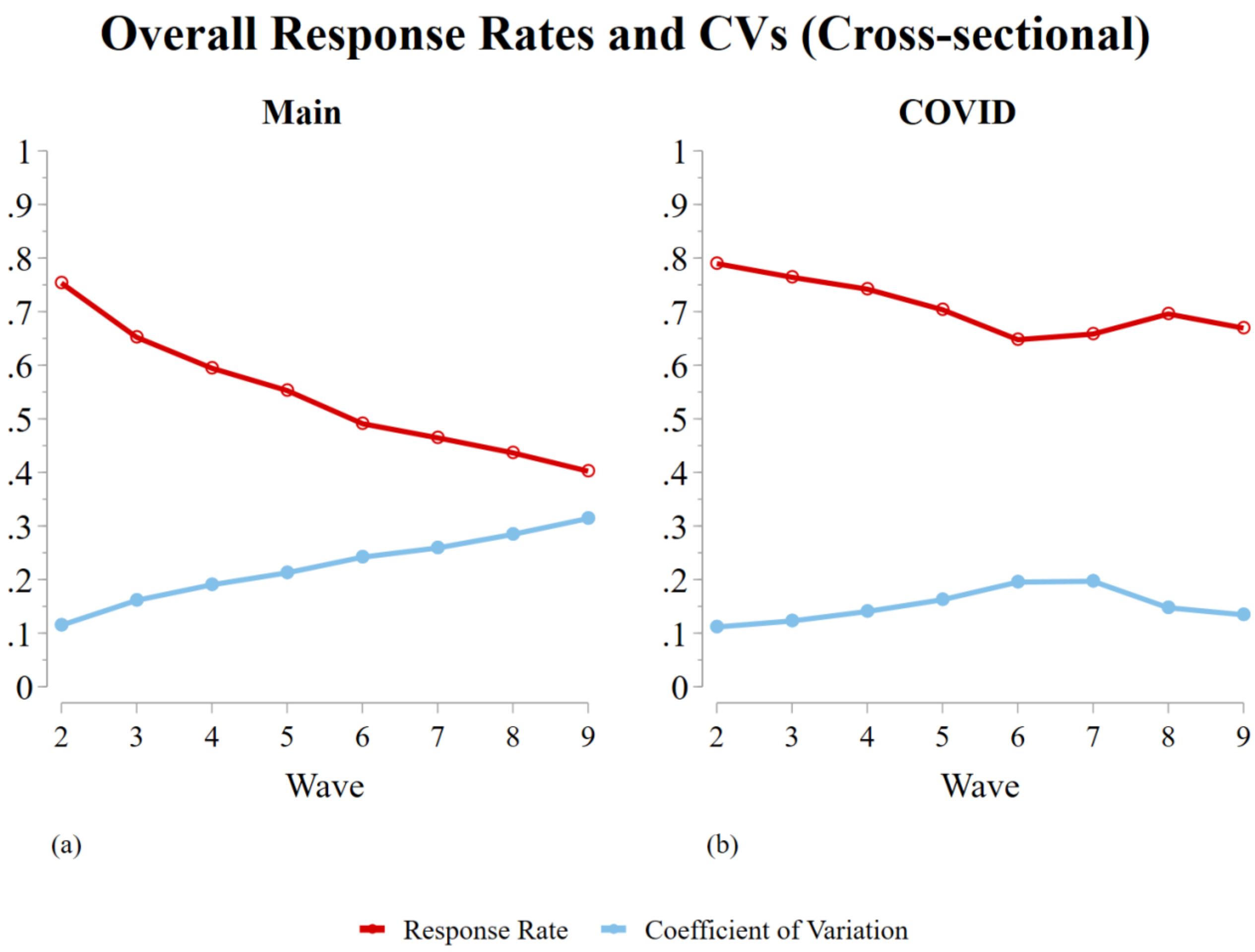

Figure B2: Response Rates and CVs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

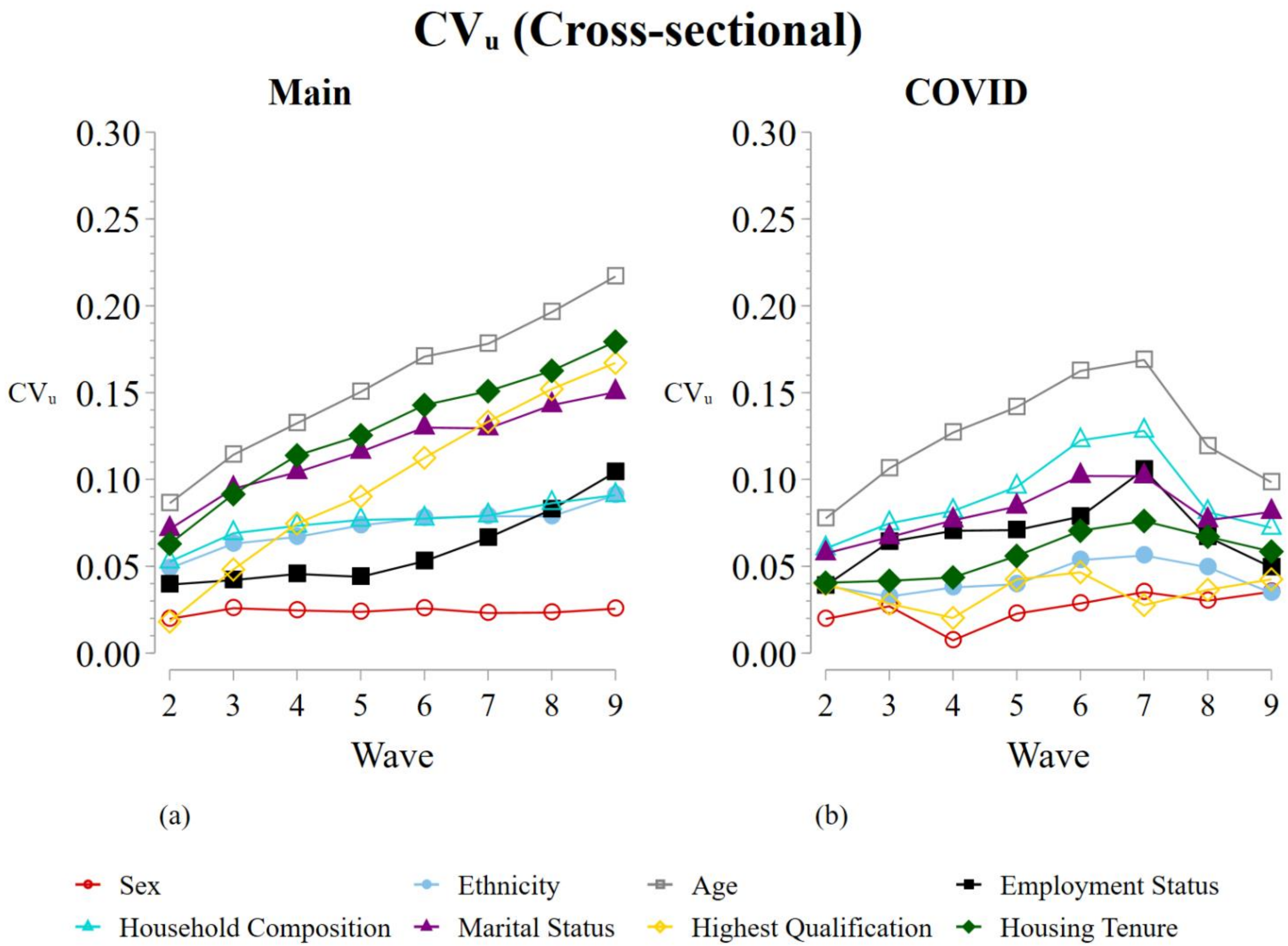

Figure B3: Partial CV_us for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

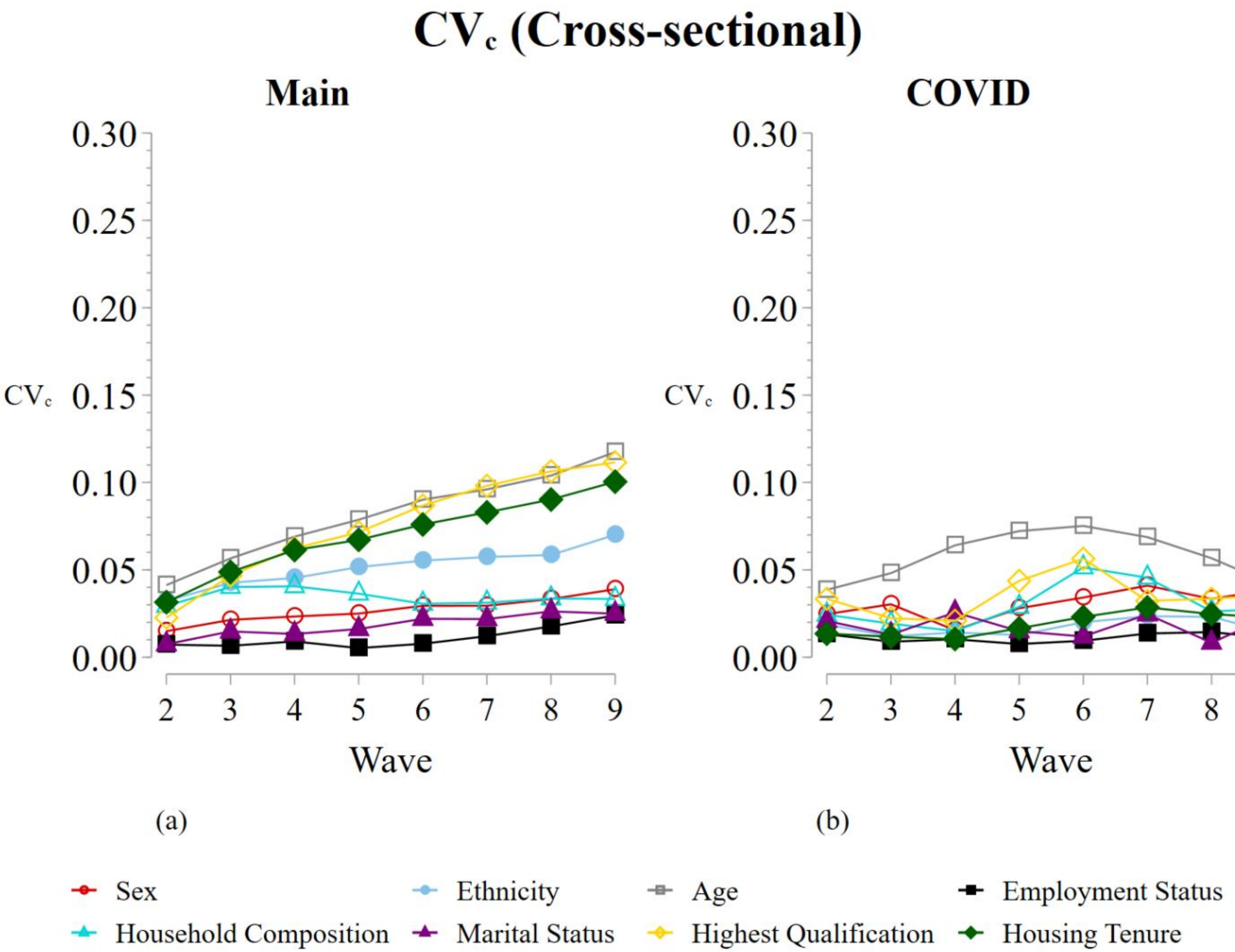

Figure B4*: Partial CV$_c$s for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional*

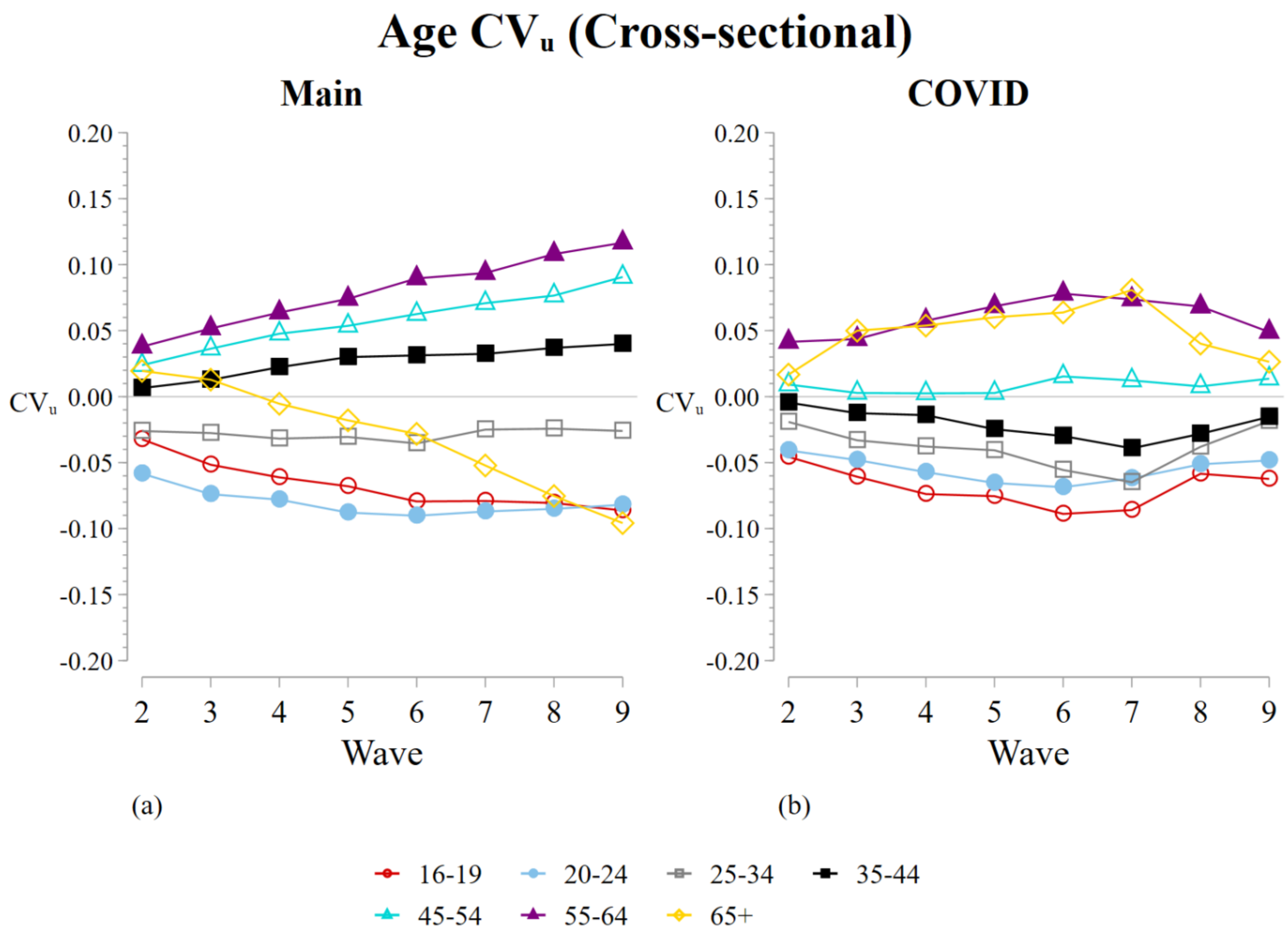

Figure B5: Partial category Age CV$_u$s for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

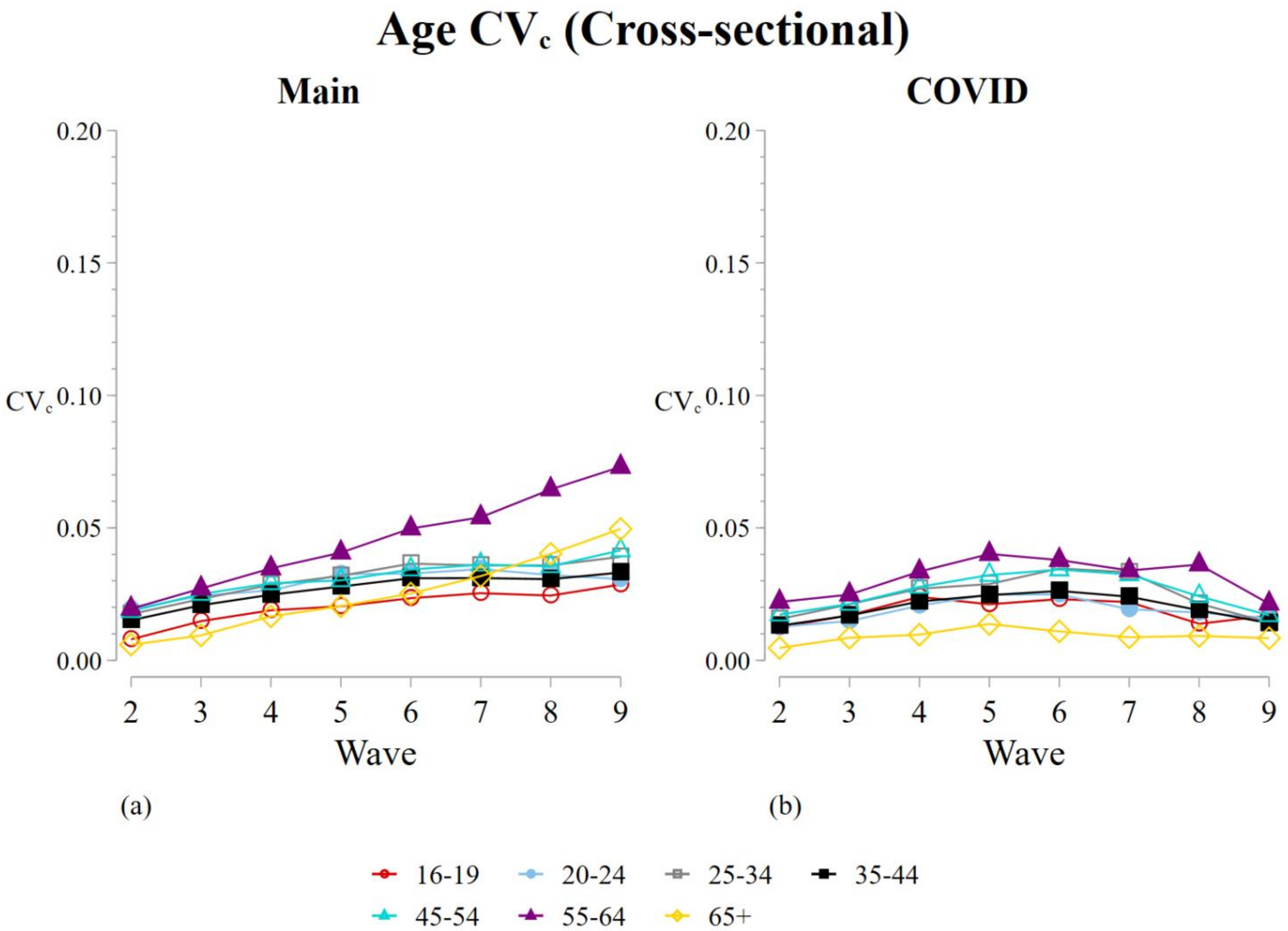

Figure B6: Partial category Age CVcs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

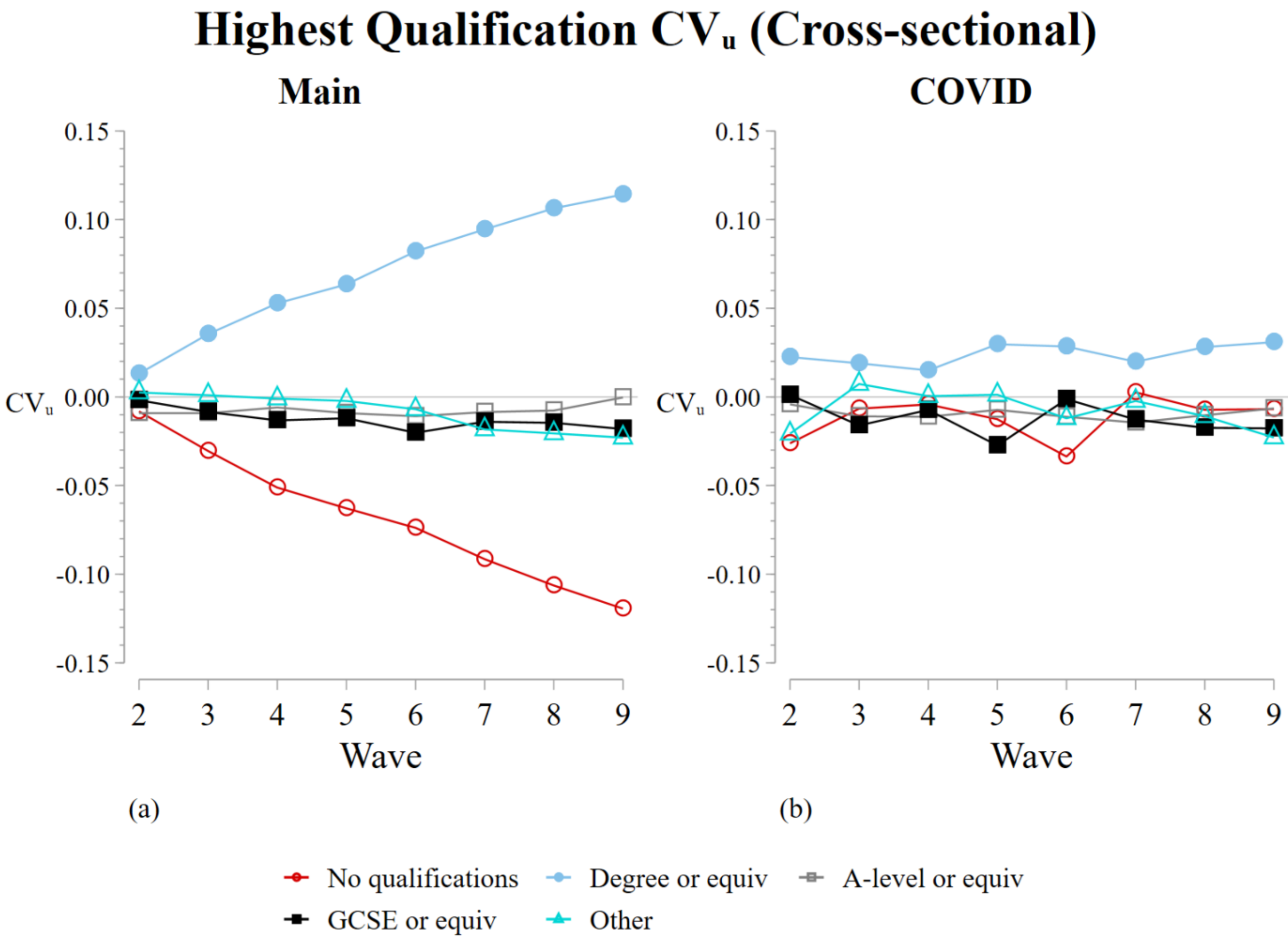

Figure B7: Partial category Highest Qualification CV_us the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

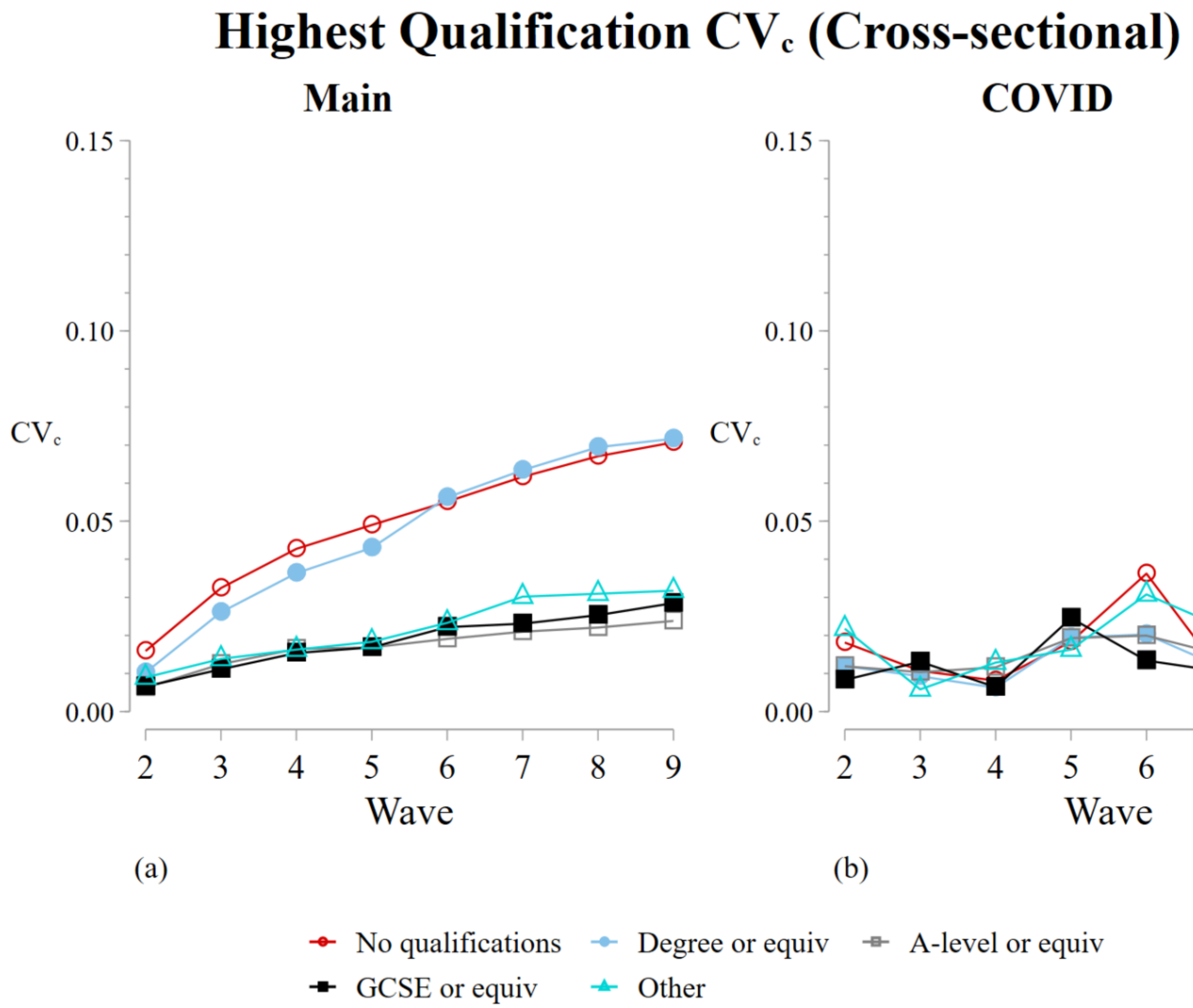

Figure B8: Partial category Highest Qualification CVcs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets cross-sectional

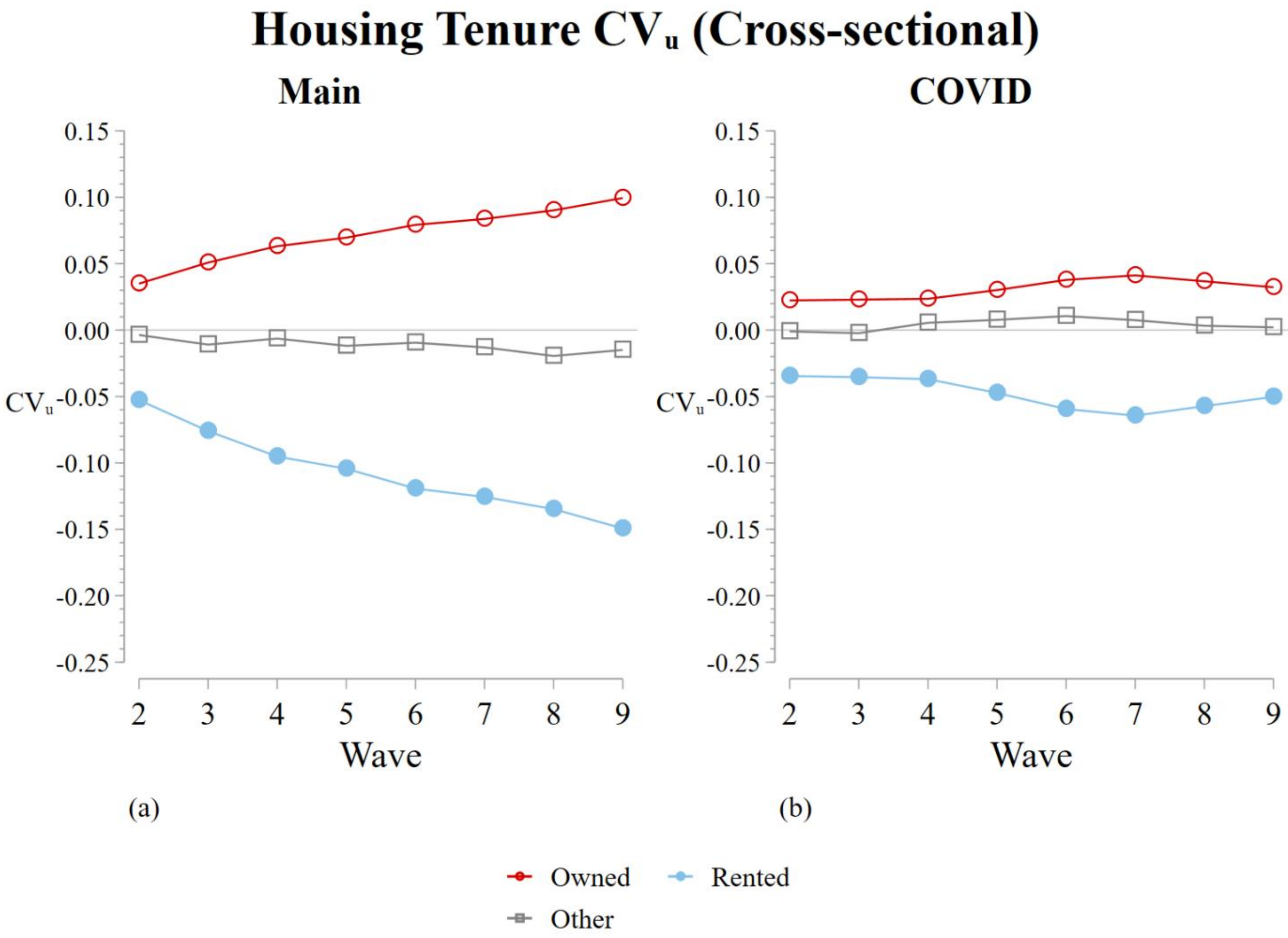

Figure B9: Partial category Housing Tenure CV_us for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

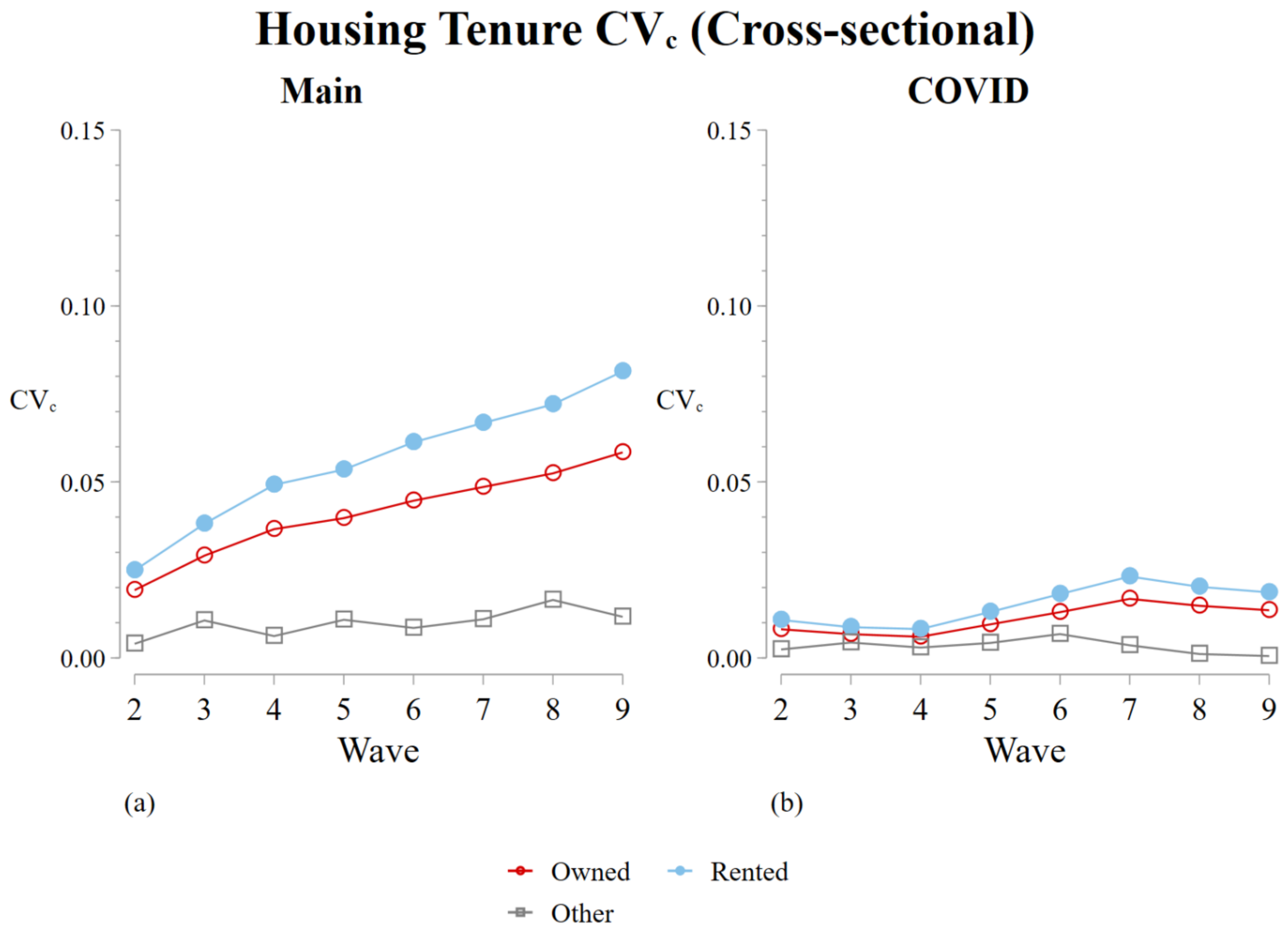

Figure B10: Partial category Housing Tenure CV_cs for the UKHLS main survey (a) and the COVID-19 Study (b) datasets, cross-sectional

Appendix C: Additional Material for Chapter 3

Appendix C: Tables

Table C1: List of covariates and UKHLS specific variable names

Covariates	UKHLS specific variable names
Sex	sex, sex_dv
Ethnicity	ethn_dv
Household Mode	hhgridmodedv
Household Composition	hhtype_dv
Household Income	fihhmnnet1_dv
Parental Response	bpx_pidp, apx_pidp, spx_pidp, fpx_pidp, ivfio
Living with Parents in Early Adulthood	bpx_pidp, apx_pidp, spx_pidp, fpx_pidp, hidp

Table C2: Average marginal effects (AME) estimated from logistic regression models of percentage of youth interviews completed and other covariates on whether the sample member had completed (1) a full adult interview age 16, (2) at least 1 full adult interview age 16-19, (3) at least 80% of the full adult interviews between ages 16-25.

	Interview Age 16				1+ Interview Age 16-19				80%+ Interviews Age 16-25			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
% of Youth Interviews Completed												
(ref: No Interviews Completed)												
Less than Half	-0.01	(0.01)	-0.02	(0.02)	-0.02	(0.01)	-0.04*	(0.02)	0.01	(0.01)	-0.01	(0.01)
Half or More	0.29***	(0.01)	0.19***	(0.01)	0.32***	(0.01)	0.19***	(0.01)	0.19***	(0.01)	0.09***	(0.01)
All	0.56***	(0.01)	0.40***	(0.01)	0.58***	(0.01)	0.39***	(0.01)	0.28***	(0.01)	0.15***	(0.01)
Female	0.05***	(0.01)	0.05***	(0.01)	0.05***	(0.01)	0.05***	(0.01)	0.07***	(0.01)	0.06***	(0.01)
Ethnicity (ref: White)												
Black	-0.04*	(0.02)	0.00	(0.02)	-0.02	(0.02)	0.02	(0.02)	-0.09***	(0.02)	-0.03	(0.02)
Indian	0.08***	(0.02)	0.08***	(0.02)	0.08***	(0.02)	0.08***	(0.02)	0.07**	(0.03)	0.06**	(0.02)
Pakistani	0.06***	(0.02)	0.09***	(0.02)	0.08***	(0.02)	0.10***	(0.02)	0.04	(0.02)	0.06***	(0.02)
Bangladeshi	0.04	(0.02)	0.07***	(0.02)	0.08***	(0.02)	0.10***	(0.02)	0.03	(0.03)	0.09***	(0.02)
Other Asian	-0.03	(0.03)	0.01	(0.03)	-0.01	(0.03)	0.02	(0.03)	-0.06*	(0.03)	-0.02	(0.03)
Mixed	-0.03	(0.02)	-0.02	(0.02)	-0.03	(0.02)	-0.01	(0.02)	-0.02	(0.02)	-0.00	(0.02)
Other	-0.08*	(0.04)	-0.03	(0.04)	-0.08*	(0.04)	-0.02	(0.04)	-0.15***	(0.02)	-0.11***	(0.03)
Household Mode during 6 Youth Years												
(ref: None Completed by Web)												
Not Eligible to Complete by Web			0.20***	(0.01)			0.27***	(0.01)			0.10***	(0.01)
< Half Completed by Web			0.27***	(0.02)			0.34***	(0.02)			0.24***	(0.02)
Half or More Completed by Web			0.23***	(0.02)			0.32***	(0.02)			0.22***	(0.02)
All Completed by Web			0.20***	(0.02)			0.30***	(0.02)			0.25***	(0.02)
Average Household Composition												
(ref: Couple, children)												
1 adult, children			-0.01	(0.01)			-0.00	(0.01)			-0.05***	(0.01)
2+ adults (no couples), children			0.01	(0.01)			0.02	(0.01)			-0.03*	(0.01)
2+ adults (at least 1 couple), children			0.01	(0.01)			0.01	(0.01)			-0.01	(0.01)
Average Household Income			0.00	(0.00)			0.00	(0.00)			0.01*	(0.00)
Parents Completed Mostly Full												
Interviews (ref: Yes)												
No Bio Parents Reported			-0.30***	(0.05)			-0.31***	(0.05)			-0.25***	(0.05)
No			-0.28***	(0.01)			-0.29***	(0.01)			-0.30***	(0.01)

Note: The marginal effects are rounded to 2 decimal places and standard errors in parentheses.
* p < .05. ** p < .01. *** p < .001.
Model 1: N = 48,684. Model 2: N = 48,544.
Model 3: N = 48,684. Model 4: N = 48,544.
Model 5: N = 48,684. Model 6: N = 48,544.

Table C3: Average marginal effects (AME) estimated from logistic regression models of age completed last youth interview and other covariates on whether the sample member had completed (1) a full adult interview age 16, (2) at least 1 full adult interview age 16-19, (3) at least 80% of the full adult interviews between ages 16-25.

	Interview Age 16				1+ Interview Age 16-19				80%+ Interviews Age 16-25			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Age Completed Last Youth Interview (ref: No Interviews Completed)												
Age 10-12	-0.10***	(0.01)	-0.11***	(0.02)	-0.15***	(0.02)	-0.14***	(0.02)	-0.02**	(0.01)	-0.04**	(0.01)
Age 13-15	0.39***	(0.01)	0.27***	(0.01)	0.41***	(0.01)	0.25***	(0.01)	0.22***	(0.01)	0.11***	(0.01)
Female	0.06***	(0.01)	0.05***	(0.01)	0.06***	(0.01)	0.05***	(0.01)	0.07***	(0.01)	0.06***	(0.01)
Ethnicity (ref: White)												
Black	-0.09***	(0.02)	-0.03	(0.02)	-0.07***	(0.02)	-0.01	(0.02)	-0.11***	(0.01)	-0.04*	(0.02)
Indian	0.05*	(0.02)	0.06*	(0.02)	0.06*	(0.02)	0.07**	(0.02)	0.05*	(0.03)	0.05**	(0.02)
Pakistani	0.00	(0.02)	0.06**	(0.02)	0.02	(0.02)	0.07***	(0.02)	0.01	(0.02)	0.05**	(0.02)
Bangladeshi	-0.02	(0.02)	0.03	(0.02)	0.02	(0.02)	0.07**	(0.02)	-0.00	(0.02)	0.07**	(0.02)
Other Asian	-0.06	(0.04)	-0.01	(0.03)	-0.05	(0.04)	0.01	(0.03)	-0.08**	(0.03)	-0.03	(0.03)
Mixed	-0.07**	(0.02)	-0.04	(0.02)	-0.07**	(0.02)	-0.03	(0.02)	-0.03	(0.02)	-0.01	(0.02)
Other	-0.13**	(0.04)	-0.05	(0.04)	-0.13**	(0.04)	-0.05	(0.04)	-0.17***	(0.02)	-0.12***	(0.03)
Household Mode during 6 Youth Years (ref: None Completed by Web)												
Not Eligible to Complete by Web			0.24***	(0.01)			0.32***	(0.01)			0.11***	(0.01)
< Half Completed by Web			0.27***	(0.02)			0.34***	(0.02)			0.23***	(0.02)
Half or More Completed by Web			0.22***	(0.02)			0.31***	(0.02)			0.21***	(0.02)
All Completed by Web			0.19***	(0.02)			0.30***	(0.02)			0.24***	(0.02)
Average Household Composition (ref: Couple, children)												
1 adult, children			-0.01	(0.01)			-0.01	(0.01)			-0.06***	(0.01)
2+ adults (no couples), children			0.01	(0.01)			0.01	(0.01)			-0.03*	(0.01)
2+ adults (at least 1 couple), children			0.01	(0.01)			0.01	(0.01)			-0.01	(0.01)
Average Household Income			0.00	(0.00)			0.00	(0.00)			0.01*	(0.00)
Parents Completed Mostly Full Interviews (ref: Yes)												
No Bio Parents Reported			-0.33***	(0.05)			-0.34***	(0.05)			-0.27***	(0.05)
No			-0.31***	(0.01)			-0.32***	(0.01)			-0.31***	(0.01)

Note: The marginal effects are rounded to 2 decimal places and standard errors in parentheses.
* p < .05. ** p < .01. *** p < .001.
Model 1: N = 48,684. Model 2: N = 48,544.
Model 3: N = 48,684. Model 4: N = 48,544.
Model 5: N = 48,684. Model 6: N = 48,544.

Table C4: Average marginal effects (AME) estimated from logistic regression models of class membership and other covariates on whether the sample member had completed (1) a full interview age 16, (2) at least 1 full interview age 16-19 (conditional on knowing household location age 16-25 and high parental response).

	Model 13		Model 14	
	1+ Interview Age 16		1+ Interview Age 16-19	
	AME	SE	AME	SE
Class Membership (ref: Class 1)	-0.12***	(0.01)	-0.08***	(0.01)
Class 2	-0.18***	(0.02)	-0.12***	(0.01)
Class 3	-0.04***	(0.01)	-0.03***	(0.01)
Class 4	0.05***	(0.01)	0.05***	(0.01)
Female				
Ethnicity (ref: White)	0.00	(0.03)	0.02	(0.02)
Black	0.04	(0.04)	0.03	(0.03)
Indian	0.02	(0.03)	0.04	(0.02)
Pakistani	0.01	(0.04)	0.04	(0.03)
Bangladeshi	-0.04	(0.06)	-0.03	(0.05)
Other Asian	-0.00	(0.03)	-0.02	(0.02)
Mixed	-0.04	(0.09)	-0.03	(0.07)
Other				
Household Mode during 6 Youth Years (ref: None Completed by Web)	0.16***	(0.02)	0.19***	(0.02)
Not Eligible to Complete by Web	0.10***	(0.03)	0.08***	(0.02)
< Half Completed by Web	0.02	(0.03)	0.04*	(0.02)
Half or More Completed by Web	0.02	(0.03)	0.07***	(0.02)
All Completed by Web				
Average Household Composition (ref: Couple, children)	-0.06***	(0.02)	-0.03*	(0.01)
1 adult, children	-0.01	(0.02)	-0.02	(0.02)
2+ adults (no couples), children	0.02	(0.02)	0.01	(0.02)
2+ adults (at least 1 couple), children	0.01*	(0.01)	0.01	(0.00)
Average Household Income				
Lived in Same Household as at Least 1 Parent in Early Adulthood (ref: 100%)	-0.71***	(0.09)	-0.45***	(0.04)
Did not live with parents	-0.05**	(0.02)	-0.04**	(0.01)
Lived with parents <80%	-0.00	(0.03)	0.04	(0.03)
Lived with parents 80%-99%	-0.12***	(0.01)	-0.08***	(0.01)

Note: The coefficients are rounded to 2 decimal places and standard errors in parentheses.
* p < .05. ** p < .01. *** p < .001.
Model 1: N = 16,516.
Model 2: N = 16,516.