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Selective Attrition and Longitudinal Consistency in Dynamic Microsimulation: Evidence from Understanding Society

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Abstract

Dynamic microsimulation models rely extensively on longitudinal household data to project long-term socio-economic, demographic, and policy outcomes. While these dynamic frameworks serve as powerful tools for economic projections, their predictive reliability depends fundamentally on the representativeness of the data used for parameterisation. Utilising 14 waves of the UK Household Longitudinal Study (UKHLS) spanning 2010 to 2024, this paper evaluates sample representativeness and attrition bias against external national benchmarks from the UK Census. We find that over time, the survey increasingly overrepresents older, white, highly educated, and partnered individuals, in a way that is only partially corrected by the provided survey weights. Probit regression models confirm a pronounced "survival bias," demonstrating that incoming entry and replacement mechanisms fail to symmetrically balance selective exit rates. Consequently, we conclude that relying solely on standard survey weights is insufficient to maintain longitudinal consistency, emphasising the necessity of integrating external alignment strategies within dynamic microsimulation frameworks.

Keywords: Simulation Methods, Simulation Modelling, Census, Household Data, Survey Methods

JEL Classification : C53, C630, C80, C83

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1. Motivation and Introduction

Dynamic microsimulation models are increasingly used to analyse the long-term distributional and fiscal consequences of demographic change, labour market transitions, health dynamics, and public policy reforms. By simulating the evolution of individuals and households over time, these models provide a framework for examining how life-course events interact with taxation, welfare systems, and behavioural responses. Within the United Kingdom, one of the models used for such analysis is SimPaths, a dynamic microsimulation model developed to study the interaction between demographic, economic, and health processes across the life course.

SimPaths (Bronka, P., et al. 2023) was designed as a comprehensive and modular simulation framework capable of projecting outcomes in multiple domains simultaneously, including education, employment, earnings, family formation, health, care provision, savings, and retirement behaviour.

The empirical foundation of SimPaths is the Understanding Society survey, officially known as the UK Household Longitudinal Study (UKHLS). Understanding Society is the largest longitudinal household survey in the United Kingdom and the successor to the British Household Panel Survey. The survey follows individuals and households, collecting detailed information on employment, income, education, health, family composition, housing, and social attitudes and how they change over time. This is crucial for dynamic microsimulation because it permits the estimation of transition probabilities affecting changes in individuals' socioeconomic circumstances over time.

In SimPaths, initial populations are constructed directly from successive waves of *Understanding Society* data spanning the survey years 2011 to 2024, and constitute alternative starting point for projections. Because the model depends fundamentally on longitudinal data, the issue of sample attrition is of paramount importance. Attrition occurs when respondents drop out of the survey over time, either temporarily or permanently. In longitudinal frameworks, attrition introduces severe bias if the propensity to drop out is systematically related to socioeconomic characteristics that govern model estimation. Empirical literature consistently demonstrates that men, younger cohorts, lower-educated respondents, and individuals with unstable employment patterns are significantly less likely to persist in longitudinal panels (Groves & Couper, 1998; Stoop, 2004; Ahern & Le Brocque, 2005; Behr et al., 2005; Nicoletti & Peracchi, 2005; Hox et al., 2012; Cabrera-Álvarez & Lynn, 2026).

Since dynamic microsimulation models rely on estimated transition probabilities and behavioural relationships derived from panel data, any non-random attrition may affect both parameter estimation and the representativeness of the initial populations, in turn affecting projections. Understanding and accounting for attrition is therefore essential for ensuring the robustness of microsimulation outcomes.

This analysis examines the role of attrition within the context of dynamic microsimulation modelling in the UK. Section 2 briefly describes the Understanding Society (UKHLS) survey and Section 3 evaluates its representativeness relative to the broader UK population. Section 4 presents empirical evidence of attrition, highlighting the demographic differences between those who remain in the survey and those who exit. Finally, Section 5 provides concluding remarks and discusses the implications for longitudinal microsimulation modelling.

2. Understanding Society and Population Representativeness

Understanding Society (UKHLS) is the principal longitudinal household survey conducted in the United Kingdom and constitutes the main data source underlying the dynamic microsimulation model SimPaths. The survey began in 2009 as the successor to the British Household Panel Survey (BHPS) and is designed to provide nationally representative longitudinal information on the socioeconomic and demographic circumstances of individuals and households across the UK. The study follows all adult members of sampled households annually and collects detailed information on employment, earnings, education, health, household composition, housing, income, benefit receipt, and subjective wellbeing. Children within sampled households are also followed as they age into adulthood, allowing the survey to capture intergenerational and life-course dynamics.

The sample design of Understanding Society combines a large general population sample with additional boost samples for ethnic minority groups and respondents from Scotland, Wales, and Northern Ireland. Survey weights are provided to adjust for unequal selection probabilities and differential non-response, with the objective of maintaining cross-sectional representativeness of the UK population over time.

We analyse 14 waves of Understanding Society, beginning in 2010 with Wave 2 of the UK Household Longitudinal Study (UKHLS). The UKHLS builds on the British Household Panel Survey (BHPS), whose active sample members were incorporated into Understanding Society from Wave 2 onwards; consequently, our analysis begins with this wave.

The survey design involves overlapping fieldwork periods, such that interviews for two consecutive waves are conducted within the same calendar year. Therefore, comparisons across consecutive calendar years should incorporate all interviews conducted during those years across the relevant waves. However, because our focus is on attrition and survey participation, the analysis is organised by survey wave rather than by calendar year.

As shown in Figure 1, the UKHLS sample size has declined steadily over the course of the survey. Wave 14 represents an exception to this trend, as a boost sample was introduced for the first time since the inception of Understanding Society, increasing the sample size.

The long-term decline in sample size reflects the challenge of retaining respondents and of recruiting new participants to replace those who leave the survey. Figure 2 illustrates trends in *Exiters*, respondents who participated in a given wave but not in the subsequent wave, and *Entrants*, respondents who participated in the current wave but not in the previous one. Across nearly all waves, the number of Exiters exceeds the number of Entrants, contributing to the overall decline in sample size. Wave 14 again constitutes an exception, as the boost sample offsets the number of respondents exiting the survey. By definition, Entrant statistics are unavailable for Wave 2 because the entire sample is newly constituted, while Exiter statistics cannot yet be calculated for Wave 15 because this would require data from Wave 16.

Figure 1: UKHLS sample size

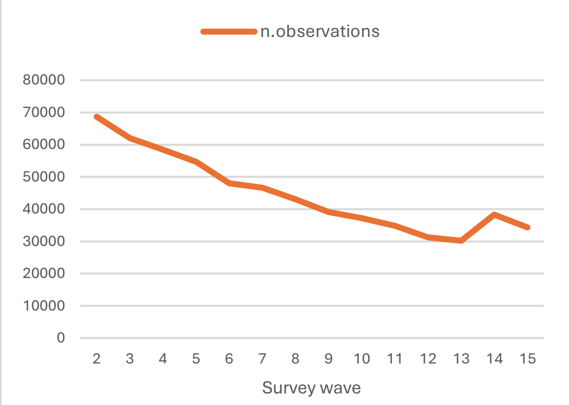
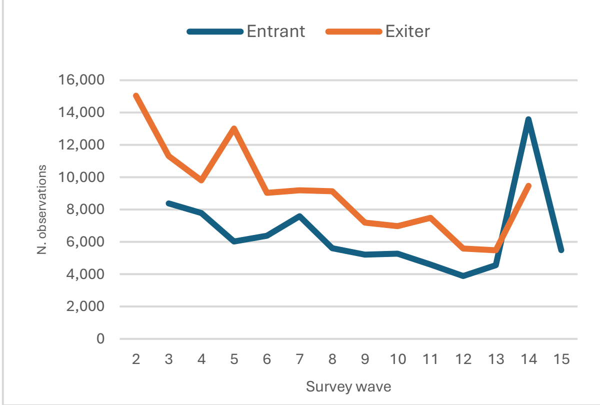


Figure 2: UKHLS entrants and exiters of the survey



Notes: UKHLS statistics are unweighted.

Respondents that exit the survey do not represent a negligible share, they vary between 17% of the sample in wave 4 and 25% of the sample in wave 14. The sample of those who are new to the survey varies between 11% of the sample in wave 5 and (exception made for the boost in wave 14 where new entrants in the survey represent 35% of respondents of the survey) 16% in wave 7 and 15.

The substantial level of respondent turnover raises an important issue for longitudinal surveys: the objective of maintaining cross-sectional representativeness is not necessarily aligned with the objective of retaining the same individuals over time. While a survey may remain representative of the contemporary population through weighting adjustments and sample refreshment, the composition of the respondent pool can nevertheless change substantially as participants leave the study and new respondents enter. At the same time, broader demographic and socioeconomic changes occurring within the population may further alter the characteristics of the groups that the survey seeks to represent.

To address these challenges, Understanding Society provides a comprehensive set of survey weights that account for unequal selection probabilities and differential patterns of non-response. Understanding Society distinguishes between cross-sectional and longitudinal weights. Cross-sectional weights are designed for analyses that use information from a single wave and are calibrated to represent the UK population at that point in time. Longitudinal weights, in contrast, are designed for analyses that follow respondents across multiple waves and adjust for cumulative non-response among individuals who remain continuously observed. Because these weights are constructed for respondents who have been continuously participating in the survey, respondents who temporarily leave the survey and later return are not included in the analysis. Thus, while cross-sectional weights prioritise representation of the population at a given point in time, longitudinal weights prioritise representation of the population that remains under continuous observation across waves.[2] In principle therefore, a microsimulation study should use transition processes estimated using longitudinal weights, and apply them to initial populations constructed using cross-sectional weights. Unfortunately however, to an extent that is meaningful for microsimulation modelling longitudinal weights fail to account for selective attrition (survey non-response), while cross-sectional weights fail to recover population representativeness under relevant dimensions of population heterogeneity.

We discuss the two issues separately in the two sections below.

3. Comparison with Census Benchmarks

To assess the extent to which Understanding Society remains representative over time, this analysis reports survey distributions in comparison with benchmarks derived from the UK Census. The Census provides the most comprehensive available description of the UK population and therefore serves as an appropriate external benchmark against which the composition of the UKHLS sample can be evaluated.

Table 1 compares selected demographic and socioeconomic characteristics observed in Understanding Society with corresponding census distributions for 2011 and 2021. The comparison focuses on dimensions that are particularly relevant for dynamic microsimulation modelling including geography, age, sex, ethnicity, partnership status, education, and economic activity.

Overall, Understanding Society remains broadly aligned with the census across geographic dimensions. The distribution of respondents across England, Wales, Scotland, and Northern Ireland closely matches census proportions in both 2011 and 2021, with differences generally below one percentage point. This suggests that the survey continues to perform well in maintaining regional representativeness, consistent with its stratified sample design and weighting procedures.

Table 1: Distribution of Census data and UKHLS survey data

[2] See Annex A1 for a discussion of the dimensions considered to construct the survey weights.

	2011			2021		
	(1) Census	(2) UKHLS	(3) Diff	(4) Census	(5) UKHLS	(6) Diff
England	83.9	83.9	0.0	84.4	83.6	-0.8
Wales	4.8	5.0	0.2	4.6	4.8	0.2
Scotland	8.4	8.5	0.1	8.1	8.4	0.3
Northern Ireland	2.9	2.7	-0.2	2.8	3.2	0.4
Female	50.9	52.9	2.0	51.1	54.4	3.3
Male	49.1	47.1	-2.0	48.9	45.6	-3.3
Up to 15	18.8	20.1	1.3	18.4	14.6	-3.8
Age 16-30	20.1	17.1	-3.0	18.3	13.3	-5.0
Age 31-40	13.2	12.9	-0.3	13.5	10.5	-3.0
Age 41-65	32.4	33.7	1.3	32.0	37.8	5.8
Age 66plus	15.4	16.2	0.8	17.6	23.9	6.4
White	87.2	89.6	2.4	83.1	91.0	7.9
Asian	6.9	5.4	-1.5	8.6	4.7	-3.9
Black	3.0	2.3	-0.7	3.7	1.6	-2.1
Other ethnic groups	2.9	2.7	-0.2	4.6	2.7	-1.9
Partnered	46.7	51.1	4.4	45.9	54.6	8.7
No qualification	23.2	25.4	2.2	18.3	16.0	-2.3
Below degree	37.7	48.9	11.2	48.1	48.4	0.3
Degree or above	39.1	25.8	-13.3	33.6	35.6	2.0
Student	9.3	6.1	-3.1	7.3	4.0	-3.3
Retired	13.9	25.5	11.6	21.6	32.8	11.2
Employed	61.6	54.3	-7.3	55.5	52.7	-2.8
Unemployed	15.2	14.1	-1.1	15.5	10.4	-5.1

Notes: Census figures are obtained from statistical tables published on the ONS website. UKHLS statistics are weighted using cross-sectional weights. Educational attainment is reported for non-students aged 16 and over. Employment status is reported for individuals aged 16 and over residing in England and Wales.

By contrast, larger discrepancies emerge across several socioeconomic characteristics, and these differences tend to increase over time. When looking at the gender dimension, women are moderately overrepresented in the survey relative to the census, with the gap between UKHLS survey and census data (columns 3 and 6 in Table 1) increasing from 2 percentage points in 2011 to 3.3 percentage points in 2021. More pronounced divergence is observed across age groups. Younger adults become increasingly underrepresented over time, with individuals aged 16–30 underrepresented by 5 percentage points in 2021 against 3 percentage points in 2011. Conversely, respondents aged 66 and above become substantially overrepresented, exceeding the census share by 6.4 percentage points in 2021 against a much lower over representation of 0.8 percentage points in 2011. These patterns are consistent with evidence from longitudinal survey research showing that younger and more mobile individuals are more likely to leave panel studies over time, while older respondents tend to display greater survey persistence.

Differences also emerge across ethnic groups. Already the 2011 distributions show some discrepancies with respect to census benchmarks, the discrepancies become even starker in 2021 with an increasing underrepresentation of ethnic minority populations within the survey sample. In particular, Asian and Black respondents are substantially underrepresented relative to Census data, while White respondents become increasingly overrepresented.

The survey additionally exhibits increasing overrepresentation of individuals in stable household and labour market positions. Respondents who are married or in a registered partnership exceed census proportions by over 8.7 percentage points in 2021, while retired individuals are overrepresented by approximately 11.2 percentage points. At the same time, employed and unemployed individuals are underrepresented relative to the Census.

Taken together, the comparisons indicate that Understanding Society remains highly valuable as a longitudinal data source and retains strong representativeness across several core dimensions. Nevertheless, the evidence also suggests that some sociodemographic characteristics diverge from census data and diverge more over time along characteristics closely associated with survey retention and attrition.

4. Attrition in Understanding Society

While the previous section evaluated the ability of the survey to represent the UK population at specific point in time (a cross-sectional perspective), analysing the longitudinal dimension allows us to capture the survey's capacity to reliably follow the same individuals over time. This distinction is critical for dynamic microsimulation modelling. A survey may appear broadly representative in a series of independent cross-sectional snapshots due to offsetting demographic shifts or cross-sectional weighting adjustments. However, it might fail to follow the life course of specific type of respondents.

To identify the dimensions most affected by attrition, we track individuals over the 14 waves of the UKHLS and examine the sociodemographic characteristics associated with survey dropout.

We first compare the characteristics of *Exiters* (those who leave the survey) against those who remain. Figures 3A through 3G present the relative frequency distributions for each group, where blue bars, *'Remain in the survey'*, and orange bars, *'Exit the survey'*, sum to 100% independently. When focusing on Education (Figure 3A), students represent a disproportionately large share of *Exiters* compared to the low, medium, or highly educated respondents.[3] Conversely, respondents with high education levels demonstrate greater survey persistence, representing a smaller share of *Exiters* than the staying population.

In terms of age (Figure 3B), younger respondents are significantly more likely to exit, representing a higher share of the *Exiter* distribution than the stayer distribution. Gender (Figure 3C) also plays a role, with men being overrepresented among those who drop out. Similarly, ethnic minorities (Figure 3D) and single respondents (Figure 3E) carry a higher relative weight among *Exiters*. In contrast, those who are employed or retired (Figure 3G) appear more stable, maintaining a higher relative weight among respondents who remain in the survey.

Figure 3: Sample distribution of respondents that remain and exit the survey

Figure 3A: Education

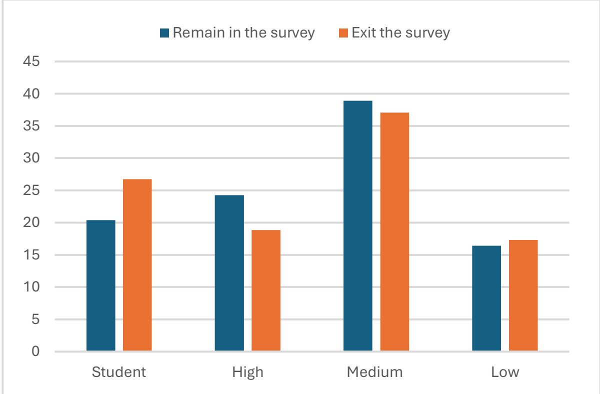


Figure 3B: Age

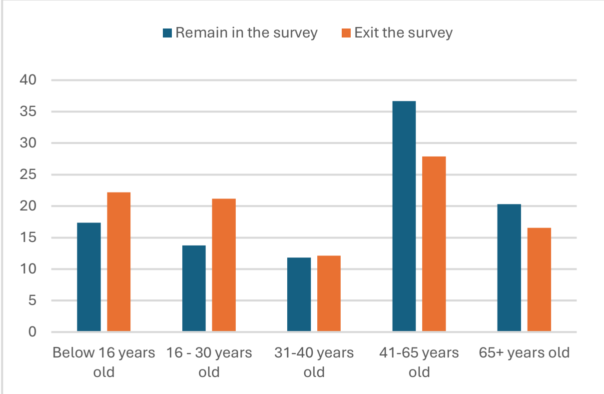


Figure 3C: Gender

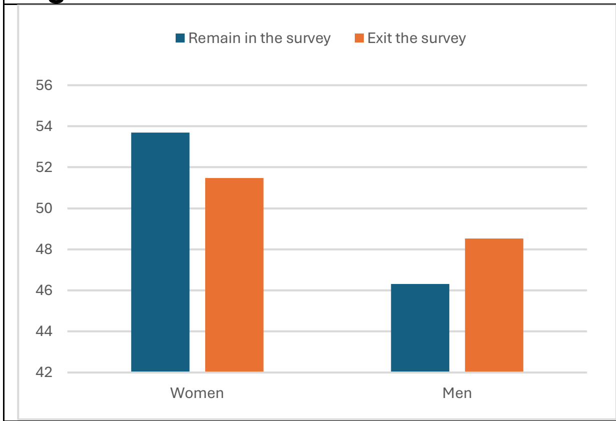


Figure 3D: Ethnicity

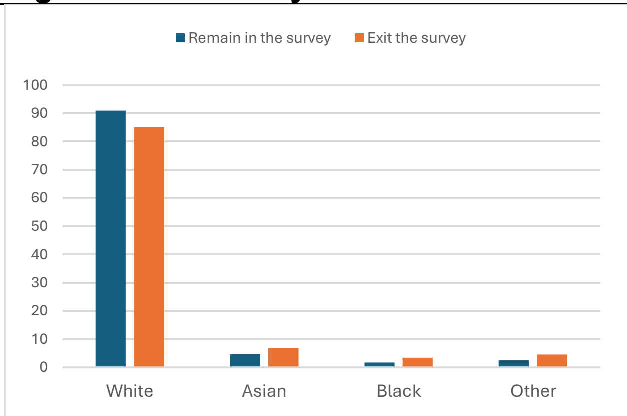
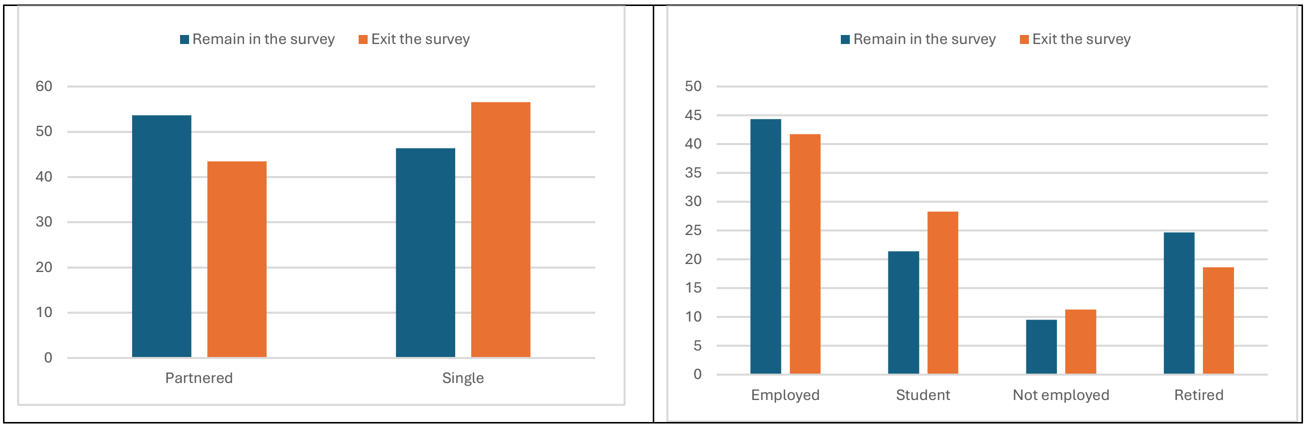


Figure 3F: Partnership

Figure 3G: Activity Status

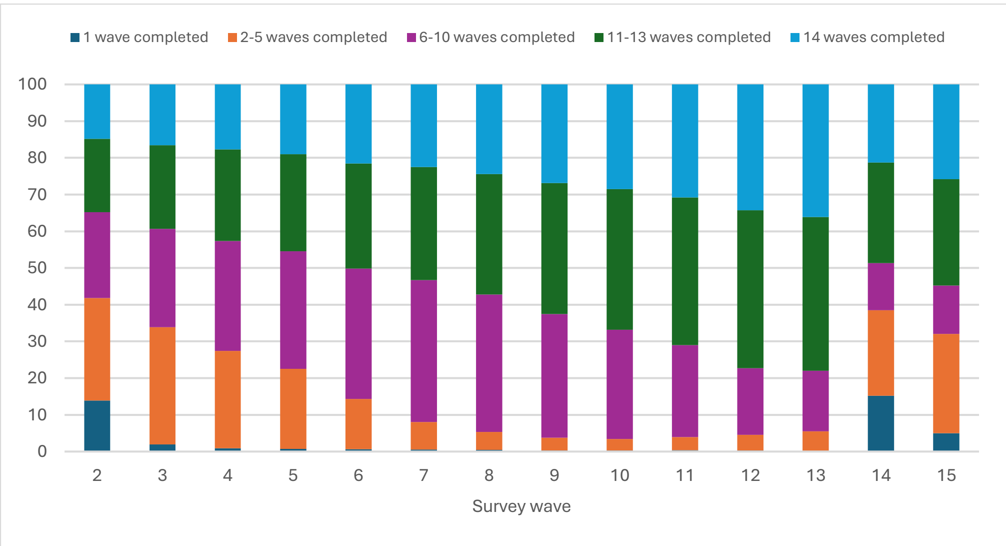
[3] Education levels are assigned post-graduation; consequently, current students are categorized separately until they exit the education system.



Notes: UKHLS statistics are weighted with cross-sectional weights (using longitudinal weights would imply dropping individuals with intermittent participation spells).

For each respondent, we compute the number of waves in which they participated over the entire period of the survey (Figure 4). Only 3.2% of the sample participated for a single wave, while approximately 23% participated for the entire duration of the study. Over half the sample, participated in more than 11 out of the 14 waves analysed. As shown in Figure 4, the number of respondents participating for more waves increases as the survey progresses, with only a negligible number of respondents exiting immediately after completing only 1 wave. However, the longitudinal sample reveals a survival bias as long-term participants become systematically different from more transient groups. Individuals with higher education, the employed or retired, women, white respondents, and those in a partnership demonstrate higher survey retention, becoming overrepresented among long stayers. Conversely, younger cohorts and ethnic minorities are more prevalent in shorter-duration groups (Annex 2).

Figure 4: Number of waves completed by survey wave



Notes: UKHLS unweighted statistics.

To formally quantify this longitudinal dynamic, we compute unconditional wave response rates (Table 2). The indicator is a binary variable constructed at the individual-wave level, which takes a value of 1 if a specific baseline participant successfully completed an interview in a given wave, and 0 otherwise. For any given wave *t,* the denominator is strictly fixed as the total number of unique individuals present at the baseline (Wave 2). The numerator is the sum of those specific baseline members who successfully returned and responded in wave *t*, regardless of whether they skipped any intermediate waves. In survey methodology, reporting the unconditional response rate is the standard approach utilized by major longitudinal studies, including the UK's *Understanding Society* (Cabrera-Álvarez & Lynn, 2026).

Table 3 reports results of unconditional wave response rates by several sociodemographic characteristics and for the entire sample. The 1st column shows that the entire panel exhibits a steady decrease in sample retention: the response rate drops to 78% in Wave 3, falls below the half-sample threshold by Wave 8 (49%), and ultimately declines to (30%) by Wave 15, indicating a high panel attrition rate across the duration of the sample.[4]

A closer inspection of these unconditional rates across socio-demographic subgroups confirms the non-random nature of attrition. Younger participants (16-30 years old) drop out at a much faster rate, retaining only 24% of their original cohort by Wave 15 compared to 42%for prime-age adults (41-65 years). Strong differences in response rates are also visible in education; individuals with high educational attainment demonstrate far greater participation (43% retention at Wave 15) than those with low education (22%). Pronounced retention gaps also emerge along the ethnic dimension; the sample of black respondents experience the sharpest decline, dropping to just 13% retention by Wave 15, while the white population maintains the highest retention at 32%. Additionally, individuals who were single at baseline or identified as students/not employed generally show lower retention across the life of the panel compared to their partnered, employed, or retired counterparts.

Table 2: Unconditional wave response rates

Wave	(1)	Education			Age				Gender	
	Overall	(2) High	(3) Medium	(4) Low	(5) 16-30 years	(6) 31-40 years	(7) 41-65 years	(8) 66+ years	(9) Women	(10) Men
2	100	100	100	100	100	100	100	100	100	100
3	78	81	79	78	70	79	82	82	79	77
4	72	76	73	71	63	73	77	73	73	71
5	66	72	67	64	57	67	72	66	67	65
6	57	63	58	54	46	58	64	56	58	56
7	54	62	56	50	43	56	62	51	55	53
8	49	59	52	46	39	52	58	46	51	48
9	45	54	47	40	35	47	54	39	46	43

4 Attrition is calculated as 1- retention rate.

10	42	53	45	37	33	45	52	35	43	40
11	39	51	43	33	30	43	50	31	40	37
12	34	48	39	28	28	39	46	25	36	32
13	33	46	37	25	26	37	45	21	35	30
14	31	45	36	24	26	37	43	19	33	29
15	30	43	34	22	24	35	42	17	32	28

Wave	Ethnicity				Partnership		Labour Market			
	(11) White	(12) Asian	(13) Black	(14) Other	(15) Partnered	(16) Single	(17) Employed	(18) Student	(19) Not employed	(20) Retired
2	100	100	100	100	100	100	100	100	100	100
3	80	70	70	68	80	76	79	75	76	82
4	74	66	60	62	75	69	74	69	70	75
5	68	58	54	56	69	63	69	62	63	68
6	59	50	43	46	61	53	60	52	55	59
7	56	47	40	42	58	50	58	49	52	55
8	51	43	34	38	54	45	54	43	47	49
9	47	36	30	32	50	40	50	38	41	44
10	44	34	25	28	48	36	49	34	39	40
11	41	30	22	25	45	33	46	30	36	36
12	37	26	19	22	41	28	43	25	31	31
13	35	24	18	21	39	27	42	24	29	27
14	33	23	15	19	38	25	41	22	28	25
15	32	23	13	18	36	24	39	21	26	23

Notes: UKHLS unweighted statistics.

To formally evaluate the statistical significance of the structural change in the composition of the sample in UKHLS, we employ probit models estimating the probability of entering or exiting the survey. Table 4 reports the results.[5] The methodology uses two distinct weighting schemes: columns (1) and (2) utilise cross-sectional weights, while columns (3) and (4) use longitudinal weights.

The regression results confirm a survival bias driven by a fundamental imbalance between entry and exit across several key dimensions. In an ideal survey environment, one would expect a replacement effect where groups with high exit rates are balanced by high entry rates. However, Table 4 reveal that replacement is rarely symmetrical.

When looking at the education dimension, where *High Education* is the reference group, under cross sectional weights (columns (1) and (2)): Low-educated respondents are substantially and significantly more likely to exit the survey. Although they have a positive coefficient in the *Entrants* equation (column 1), the marginal effect reported in Annex 3 is small and statistically insignificant. Under longitudinal weights (columns (3) and (4)) low-educated panel members are +3.9 percentage points more likely to exit, with virtually zero offset in recruitment. This

[5] Marginal effects are reported in Annex 3.

confirms that the survey is failing to recruit or retain lower educated individuals at a rate that offsets the increasing concentration of highly educated respondents.

A similar asymmetrical pattern appears for partnership status. Compared to partnered respondents, single individuals are significantly more likely to exit the survey under both weighting schemes

Across both weighting schemes, older respondents show a statistically significant, negative probability of exiting. Interestingly, the marginal probability of entering is also slightly negative, meaning younger cohorts are more likely to enter but exit at a far higher rate. Women are significantly less likely to exit than men, under both weighting schemes. Under the longitudinal weights coefficients are not statistically significant for entering into the survey, while with cross sectional weights the probability of entering the sample for female respondents is lower compared to the male counterpart but the larger absolute magnitude of the exit coefficient ensures that the female sub-sample continues to grow relative to the male sample.

Crucially, the income distribution yields a stark attrition gradient with the probability of exiting the survey decreasing in magnitude along the income distribution. While this exit trend remains consistent across both weighting schemes, the choice of weight drastically alters the observed recruitment patterns. Under cross-sectional weights, higher-income households display a significantly lower probability of entering the survey compared to those in the poorest quintile. However, under longitudinal weights, this dynamic reverses. Hence, the poorest households are cross-sectionally the most likely to enter but also the most likely to drop out. Under longitudinal weights, which are available only for the respondents who continuously answer to different survey rounds, the richer respondents are both significantly more likely to be recruited into the longitudinal baseline and less likely to exit the survey.

When looking at the ethnicity dimension, with respect to white respondents which is the reference group, ethnic minorities show significantly higher probabilities of exiting the survey with black respondents displaying the highest probability of exiting the survey among the minorities.

The number of waves participated exerts a small but highly significant negative marginal effect on exiting the survey, suggesting that the marginal probability of exit decreases as respondents participate in the survey.

Table 3: Regression estimates

	(1) Entrants, Cross-sectional	(2) Exiters, Cross-sectional	(3) Entrants, Longitudinal	(4) Exiters, Longitudinal
Age	-0.010***	-0.003***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.001)	(0.000)
Women	-0.049***	-0.062***	-0.011	-0.030***
	(0.006)	(0.005)	(0.012)	(0.009)

Student	0.041	0.060*	0.101*	0.057
	(0.031)	(0.024)	(0.044)	(0.038)
Medium education	-0.012	0.087***	-0.005	0.066***
	(0.008)	(0.007)	(0.016)	(0.011)
Low education	0.008	0.180***	0.002	0.167***
	(0.011)	(0.009)	(0.020)	(0.014)
Single	-0.015*	-0.119***	-0.049***	-0.109***
	(0.007)	(0.006)	(0.014)	(0.010)
Student	-0.192***	-0.049*	0.350***	-0.038
	(0.031)	(0.023)	(0.042)	(0.035)
Not employed	-0.024*	-0.102***	0.109***	-0.056***
	(0.012)	(0.011)	(0.023)	(0.016)
Retired	-0.048***	-0.157***	0.051*	-0.038**
	(0.011)	(0.010)	(0.022)	(0.015)
2nd Quintile	-0.077***	-0.060***	0.083***	-0.026
	(0.010)	(0.010)	(0.024)	(0.016)
3rd Quintile	-0.112***	-0.177***	0.133***	-0.126***
	(0.011)	(0.010)	(0.025)	(0.017)
4th Quintile	-0.125***	-0.251***	0.165***	-0.182***
	(0.011)	(0.010)	(0.026)	(0.018)
5th Quintile	-0.141***	-0.305***	0.190***	-0.247***
	(0.012)	(0.011)	(0.027)	(0.019)
Asian	0.315***	0.165***	0.050*	0.105***
	(0.014)	(0.010)	(0.024)	(0.018)
Black	0.422***	0.271***	0.053	0.155***
	(0.022)	(0.016)	(0.038)	(0.026)
Other	0.402***	0.141***	0.048	0.050
	(0.016)	(0.015)	(0.046)	(0.031)
London	0.040***	0.057***	0.072**	0.078***
	(0.011)	(0.010)	(0.022)	(0.016)
Wales	0.069***	0.077***	0.018	0.127***
	(0.011)	(0.010)	(0.030)	(0.020)
Scotland	0.029**	0.021*	0.066**	0.077***
	(0.010)	(0.009)	(0.025)	(0.017)
Northern Ireland	0.082***	0.032**	-0.035	0.101***
	(0.014)	(0.010)	(0.033)	(0.022)
N. of waves participated until now		-0.007***		-0.007***
		(0.001)		(0.001)
Constant	-0.289***	-0.659***	-1.481***	-0.636***
	(0.031)	(0.028)	(0.076)	(0.051)
Observations	557340	490719	210032	200149

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While the data indicates that some degree of replacement takes place, these entry rates tend to fail to compensate for the lower exit patterns. This fundamental asymmetry means that new recruits do not sufficiently offset the specific selective attrition occurring over time. Consequently, the active sample with time suffers of a progressive loss of representativeness.

5. Discussion

To contextualize our findings, it is essential to emphasize how our analytical framework departs from existing survey quality evaluations of Understanding Society (UKHLS), most notably work by Lynn & Borkowska (2018) and subsequent annual attrition reports. While these studies provide benchmarks on general panel retention within the survey, our approach differs in four aspects.

First, whereas Lynn & Borkowska (2018) limit their Census comparisons primarily to the historical British Household Panel Survey (BHPS), our study conducts the analysis for the entire UKHLS sample, directly evaluating cross-sectional representativeness against both the 2011 and 2021 UK Censuses. This design reflects our core objective: rather than isolating the performance of individual sub-sample components, we assess the overall representativeness of the survey.

Second, rather than analysing only respondents who drop out from the survey, as in Alvarez, P. C. and Lynn, P. (2026), we analyse full sample turnover by jointly evaluating Exiters and Entrants across all 14 waves. This bidirectional approach allows us to understand the role of sample refreshment as a symmetric replacement mechanism for selective attrition.

Third, we formalise participation dynamics through multivariate probit regressions with both cross-sectional and longitudinal weighting schemes hence finding which of these dimensions are statistically significant.

Finally, this approach allows us to directly evaluate how selective panel attrition distorts both the baseline populations used to initialize SimPaths and the estimation of transition probabilities that are essential for dynamic microsimulation.

6. Conclusions

This analysis demonstrates that while the UK Household Longitudinal Study (UKHLS) remains an invaluable tool for capturing life-course transitions, it suffers from cross-sectional under-representation and panel attrition. Over the 14 waves analysed, the active panel reports discrepancies from national benchmarks established by the 2011 and 2021 UK censuses. The respondents who remain continuously under observation tend to be older, white, highly educated, and partnered. Conversely, the survey experiences an under representation of younger, male, lower-educated, and ethnic minority respondents. Crucially, these patterns are not isolated discrepancies limited to the two census years; rather, they are the result of a cumulative, non-random attrition process, as confirmed by our longitudinal analysis of unconditional wave response rates.

Our probit regression framework confirms that this phenomenon is statistically significant and cannot be fully addressed by cross-sectional and longitudinal weights. In fact, the demographic profile of incoming entrants fails to symmetrically balance the selective attrition of exiting panel members.

For dynamic microsimulation models like SimPaths, these findings have important implications. The first one concerns transition probabilities. Because behavioural equations are estimated from a survey panel, the estimated parameters risk being representative of the more stable demographics represented in the survey.

When a baseline population is projected decades into the future, initialisation biases regarding age, education, and ethnicity may compound in the future. This can create skewed fiscal and distributional forecasts which need to be addressed when doing long-term analysis.

Ultimately, while cross-sectional and longitudinal weights are useful tools for adjusting survey representativeness, this analysis proves they do not fully eliminate attrition bias or maintain cross-sectional alignment over time. If microsimulation models are to provide robust, realistic policy guidance for the UK, researchers cannot rely on survey weights alone. Instead, they must actively implement external alignment techniques that allow the simulation process to meet national population targets throughout the projection horizon.

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Annexes

Annex 1: UK Household Longitudinal Study (UKHLS) weighting methodology

The Understanding Society (UKHLS) survey weights account for unequal selection probabilities, non-response, and attrition across waves. As outlined by Lynn and Kaminska (2010), the weighting strategy follows a three-step sequence:

1. Design Weights: Account for differing sampling probabilities across the various sub-samples included in UKHLS.
2. Non-Response Adjustments: weights computed at both household and individual level to capture nonresponse propensities.
3. Post-Stratification: construct weights that allow to align the survey information with known population distributions.

Below, we present the technical details of the weighting procedure used for the British Household Panel Survey (BHPS), one of the samples of UKHLS (Taylor et al., 2018). To our knowledge, the BHPS user manual provides the most detailed description of the weighting framework, including the auxiliary variables used to construct the different survey weights. Although the BHPS represents only one of the UKHLS samples, we present here its weighting methodology as a proxy for the broader UKHLS weighting framework, given the absence of equivalent technical documentation for the other sample components.

1.1. Design Weights

For the first wave of the BHPS a two-stage stratified sample design was adopted.

The first step consisted in the selection of 250 Primary Sampling Units (PSUs), defined as postcode sectors containing an average of 2,500 delivery points which correspond to addresses. Secondly, there was a selection of around of 33 delivery points per sampled PSU.

To correct for differential representation resulting from this design, design weights are calculated as the inverse of a unit's total selection probability. The probability of selecting a specific household γ located at delivery point βwithin PSU $\alpha$is defined as:

$$P(\alpha\beta\gamma) = P(\alpha) \times P(\beta \mid \alpha) \times P(\gamma \mid \alpha\beta)$$

Where:

- $P(\alpha)$is the probability of selecting the PSU.
- $P(\beta \mid \alpha)$is the conditional probability of selecting the delivery point within that PSU.
- $P(\gamma \mid \alpha\beta)$is the conditional probability of selecting the household within that delivery point.

1.2. Household and individual non response

To compensate for non-responding households in Wave 1, weighting classes are constructed using auxiliary data available for both responding and non-responding households (region characteristics, PSU socio-economic characteristics, and dwelling type). Adjustments are handled under two scenarios:

- Unknown Dwelling Type**:** Weighting classes are formed via a cross-classification of region and PSU socio-economic profiles (categorized by low, medium, and high percentages of heads of household in professional occupations). Responding households are weighted up so that the total weighted count in each class equals the sum of responding and non-responding households.
- Known Dwelling Type**:** Weighting classes defined above are further subdivided by the specific accommodation type observed during fieldwork.

1.3. Individual non-response adjustment

In the cases where a household responded but specific eligible individuals within that household did not participate, a within-household non-response adjustment is applied.

First a logistic regression model predicts the binary outcome responding to the survey. The model incorporates region, housing tenure, an affluence measure, the number of eligible individuals in the household, marital status, employment status, age, sex. The individual non-response weight is the inverse of the predicted response probability trimmed to a maximum value of 1.75.

A post stratification adjustment, at the household level, is implemented to adjust marginal distributions to match known population distributions. This first stratification considers the distributions of housing tenure, household size, and car ownership. Finally, a second post-stratification considers individual characteristic based on age and sex population tables. Because this is executed at the individual level, weights may vary among individuals living within the same household.

1.4.4. Longitudinal weights

The longitudinal respondent weights are applied to respondents who participate consecutively in different survey rounds. At each wave these respondents are re-weighted to consider respondents lost through refusal or some other form of sample attrition. Thus, the longitudinal weight at any wave is the product of the sequence of attrition weights up to the last wave in which the respondent participated. Weighting was carried out using a weighting class method where respondents and non-respondents were classified by a number of variables considered to be explanatory of attrition. Automatic interaction detection programme (SPSS CHAID) was used to split respondents and non-respondents into groups defined by variables associated with non-response. Variables used in these adjustments included: Whether moved from the previous wave address; individual characteristics such as age, sex, employment status, income total and composition, race, educational qualifications, etc. and household characteristics such are region, tenure, number of cars and ownership of consumer durables. The initial attrition weight was defined as the product of the previous wave longitudinal respondent weight (before post-stratification) and the adjustment factors defined based on the weighting steps described above. After this, a post-stratification adjustment was added so that the wave 1 characteristics of the surviving sample corresponded to population distribution in terms of age, sex, housing tenure, numbers of cars and household size.

1.5.5. Cross sectional weights after wave one

To enable cross sectional analysis of individual for subsequent waves, cross sectional weights are derived to include new entrants who lack initial baseline weights. Because the inclusion and response probabilities of new entrants are unknown at entry, a fair shares approach is employed to distribute weight across household members. The first stage of this derivation adjusts the weight of individuals present at Wave 1 to account for attrition using similar weighting class method as those defined above for longitudinal respondents. Once these attrition factors were calculated, weights were defined for original sample members based on the Wave 1 defining the fair share weights for all eligible individuals, including new entrants, giving the final cross-sectional individual weight. A cross-sectional household weight is also provided and is equal to the cross-sectional individual weight subject to rescaling back to the total number of households.

Annex A2: Number of waves completed by sociodemographic characteristics

Figure 5A: Education

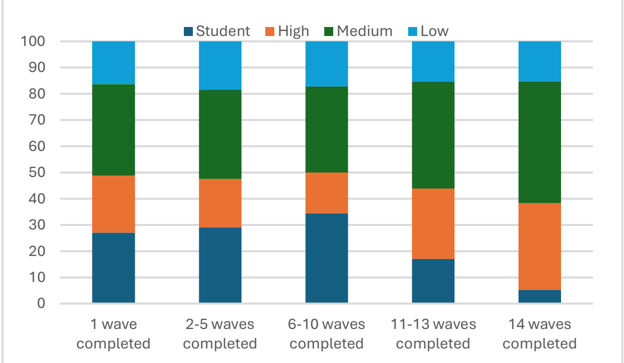


Figure 5B: Age

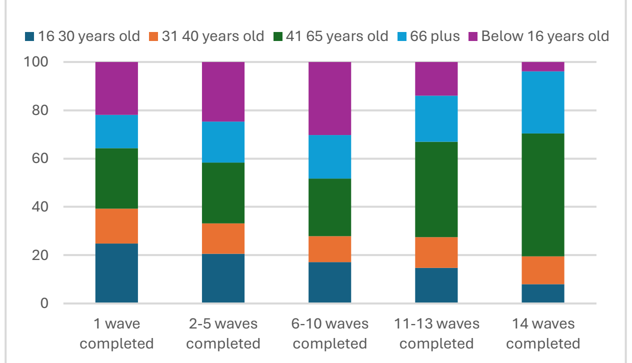
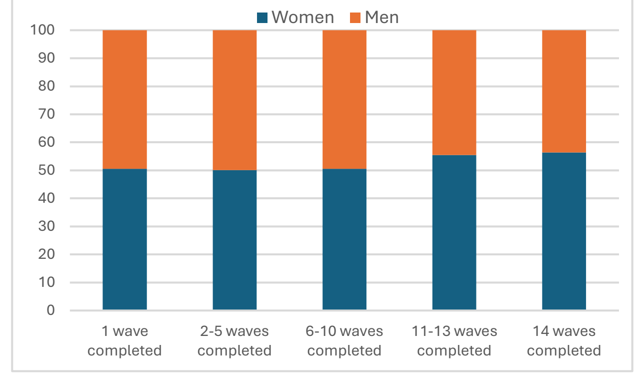


Figure 5C: Gender

Figure 5D: Ethnicity



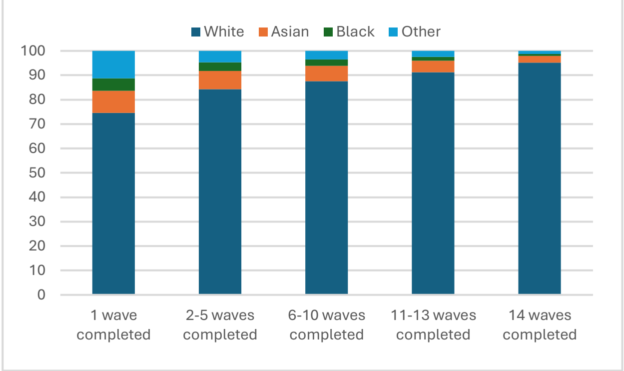


Figure 5F: Partnership

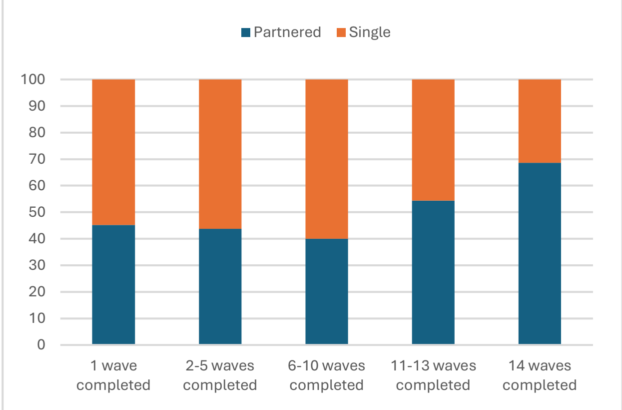
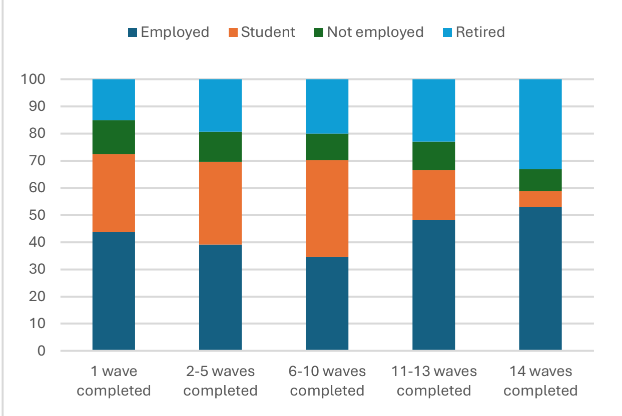


Figure 5G: Activity Status



Annex A3: Average Marginal Effects from Probit Model

	(1) Entrants, cross	(2) Exiters, cross	(3) Entrants, long	(4) Exiters, long
Age	-0.002***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Women	-0.010***	-0.016***	-0.001	-0.007***
	(0.001)	(0.001)	(0.001)	(0.002)
Student	0.008	0.015*	0.009*	0.013
	(0.006)	(0.006)	(0.004)	(0.009)
Medium education	-0.003	0.022***	-0.000	0.015***
	(0.002)	(0.002)	(0.001)	(0.003)
Low education	0.002	0.045***	0.000	0.039***
	(0.002)	(0.002)	(0.002)	(0.003)
Single	0.003*	0.030***	0.004***	0.025***
	(0.001)	(0.002)	(0.001)	(0.002)
	-0.039***	-0.012*	0.031***	-0.009
	(0.006)	(0.006)	(0.004)	(0.008)
Student				
	-0.005*	-0.025***	0.010***	-0.013***
	(0.002)	(0.003)	(0.002)	(0.004)
Not employed				
	-0.010***	-0.039***	0.004*	-0.009**
	(0.002)	(0.002)	(0.002)	(0.003)
Retired				
	-0.016***	-0.015***	0.007***	-0.006
	(0.002)	(0.002)	(0.002)	(0.004)

2nd Quintile				
	-0.023***	-0.044***	0.012***	-0.029***
	(0.002)	(0.003)	(0.002)	(0.004)
3rd Quintile				
	-0.026***	-0.063***	0.015***	-0.042***
	(0.002)	(0.003)	(0.002)	(0.004)
4th Quintile				
	-0.029***	-0.076***	0.017***	-0.057***
	(0.002)	(0.003)	(0.002)	(0.004)
5th Quintile				
	0.065***	0.041***	0.004*	0.024***
Asian	(0.003)	(0.003)	(0.002)	(0.004)
	0.086***	0.068***	0.005	0.036***
Black	(0.004)	(0.004)	(0.003)	(0.006)
	0.082***	0.035***	0.004	0.011
Other	(0.003)	(0.004)	(0.004)	(0.007)
	0.008***	0.014***	0.006**	0.018***
	(0.002)	(0.002)	(0.002)	(0.004)
London				
	0.014***	0.019***	0.002	0.029***
	(0.002)	(0.002)	(0.003)	(0.005)
Wales				
	0.006**	0.005*	0.006**	0.018***
	(0.002)	(0.002)	(0.002)	(0.004)
Scotland				
	0.017***	0.008**	-0.003	0.023***
	(0.003)	(0.003)	(0.003)	(0.005)
Northern Ireland				
		-0.002***		-0.002***
N. of waves participated until now		(0.000)		(0.000)
	557340	490719	210032	200149

* p < 0.05, ** p < 0.01, *** p < 0.001