Revisiting Sample Bias in the UK's Annual Survey of Hours and Earnings, with Implications for Estimates of Low Pay and the Bite of the National Living Wage

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Abstract

The Annual Survey of Hours and Earnings (ASHE) is based on an annual one per cent sample of employee jobs and provides many of the UK's official earnings statistics. These statistics are generated using official weights designed to make the achieved sample in each year representative of the population of employee jobs in Britain by gender, age, occupation, and region. However, we find that jobs in small, young, private-sector organisations remain under-represented after weighting. Additionally, there is evidence of systematic year-to-year longitudinal attrition among employees who remain in scope, for which no official weighting adjustment exists. We develop new weights to address these issues, demonstrating their importance through policy-relevant examples. Our new estimates suggest that the bite of the National Living Wage is greater, and that progress toward the target for eradicating low pay has been faster, than previously understood.

Keywords: Earnings; Non-response bias; Attrition; Survey weighting; Low pay; National Living Wage

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1 Introduction

The Annual Survey of Hours and Earnings (ASHE), conducted by the UK Office for National Statistics (ONS), is an important source of official statistics on earnings and working hours in the UK labour market (see, for example, ONS, 2023b, 2023c). ASHE is also widely used to inform policymaking and policy evaluation across government. It is used *inter alia* by the Low Pay Commission (LPC) to monitor the impact of the minimum wage, by the Department for Work and Pensions (DWP) to analyse pension changes, and by the Office of Manpower Economics to inform public sector pay reviews (ONS, 2018).

The issued sample for ASHE comprises a one per cent simple random sample of employee jobs, drawn from tax and social security records. Information on each sampled employee's earnings and hours is provided by their employer, who is statutorily required to respond. Nevertheless, the annual yield from the issued sample is typically around two-thirds.

ASHE was introduced in 2004 to replace the New Earnings Survey (NES) after an official review identified that the NES was unrepresentative of the population of employee jobs (ONS, 2002; Bird, 2004). Although ASHE shares many common features with the NES, a key innovation was the introduction of cross-sectional survey weights, which adjust the profile of the achieved sample so that it is representative of the population of employee jobs in terms of gender, age, occupation, and region. However, the absence of any employer characteristics from the weighting scheme raises the possibility that the achieved sample may have residual biases, causing it to over- or under-represent jobs from particular types of employers. We link data from ASHE to the UK's official business register to investigate this issue. We find that jobs in smaller organisations, younger organisations and those in the private sector are under-represented in the annual samples from ASHE relative to their prevalence in the wider economy, even after applying the official ASHE weights. To address this, we use a raking approach (Deville et al., 1993) to derive new cross-sectional weights that take account of these observed biases.

We also investigate longitudinal attrition in ASHE. The sample design for ASHE implies that an employee will be selected into the issued sample each year that they hold an employee job. This sample design thus has the potential to generate repeated annual observations for these individuals, a characteristic that has been exploited to investigate employees' earnings transitions and job mobility over successive years (e.g. ONS, 2019; Elsby et al., 2016; Dickens et al., 2015; Schaefer and Singleton, 2019; Bell et al., 2022). However, to our knowledge, the ONS makes no explicit attempts to maximise response rates among those who responded in the previous period, as would happen in a typical longitudinal survey. This may help to explain why the rate of sample attrition is relatively high between years. We use the employee identifiers in ASHE to link records over time and estimate rates of longitudinal attrition across each pair of years, after using the Annual Population Survey to account for an employee's likelihood of moving out of employee status (and hence out of scope for ASHE). We find that younger employees, those on low wages, and those working relatively few hours are more likely to drop out of the ASHE sample between successive years, even after accounting for their likelihood of leaving employee status. To address this, we use a calibration approach to construct longitudinal two-period weights for ASHE.

We use the new cross-sectional and longitudinal weights to re-estimate the coverage rate and bite of the National Minimum Wage and National Living Wage. ASHE is the main data source used by the ONS and the Low Pay Commission to estimate the incidence of low pay, making it a vital component in decision making over the future level of the minimum wage and broader policies aimed at supporting living standards. Our findings suggest that that the percentage of jobs paid at or below the National Living Wage (NLW) is under-estimated by around one fifth if the cross-sectional response biases that we identified in ASHE are not accounted for. The bite of the NLW is also under-estimated, such that the Government's targets for this measure have been reached more quickly than previously thought. In contrast, the share of employees moving off the minimum wage to higher-paid employment each year is not substantively affected by the choice of weights.

Our findings contribute to the literature on rates and patterns of minimum wage employment and low pay in the UK (e.g. Dickens et al., 2015; Aitken et al., 2019; Low Pay Commission, 2022; Giupponi et al., 2024). They also contribute to a broader literature on the nature, detection, and removal of non-response biases in business surveys (e.g. Willimack et al., 2002; Willimack and Snijkers, 2013).

2 Background

When introduced in 2004, ASHE used the same sampling frame as the NES (HRMC's PAYE Register) and collected many of the same data items. However, key elements of the survey methodology were changed in line with recommendations made in the National Statistics Quality Review of the Distribution of Earnings Statistics (ONS, 2002). The review identified that statistics generated from the NES were likely to be biased because the survey missed significant numbers of employees that changed job during the three months that typically elapsed between sample selection in January and the survey reference date in April. Additionally, responses to the NES were not weighted to the population of employee jobs. The revised sample design and weighting approach developed for ASHE aimed to address both these issues, with the explicit aim of making ASHE the definitive source for low pay statistics (see Bird, 2004; Pont, 2007).

2.1 ASHE sample design

The target population for ASHE is all employee jobs in the UK, across all industries and occupations. The sample for the survey is drawn from the UK's official Pay-As-You-Earn (PAYE) register. PAYE is the system used by HM Revenue and Customs to collect income tax and social security contributions for employee jobs. Employers are legally required to operate PAYE if the earnings of any of their employees reaches the National Insurance (NI) Lower Earnings Limit (£123 per week in 2023/24). They must then report payments and deductions for all their employees to HMRC on or before each payday. The PAYE register, therefore, provides a comprehensive and up-to-date record of employee jobs in the UK. A one per cent sample of jobs is drawn from the register by selecting all PAYE-registered jobs held by employees with a National Insurance (NI) number ending in a particular two digits. If a sample member holds multiple jobs, all are selected.

An initial sample of jobs is selected in January of each year. A second extract is then taken in April to identify instances where a sample member has started a new job or changed employer since the initial sample was drawn. The issued sample may then be considered a one per cent random sample of all employee jobs in existence in April of the survey year. The sample design also means that individuals with eligible NI numbers are selected into the issued sample each year that they are in PAYE employment at the time of sample selection.

The survey itself is completed by employers. To obtain their contact details, the sample drawn from the PAYE register is matched against the ONS Inter Departmental Business Register

(IDBR). Survey questionnaires are typically dispatched to employers in the second half of April and ask for information on the paid working hours and earnings of the sampled employee job for the pay period that includes a specific reference date (typically the second or third Wednesday of April). A specific date is chosen so that all respondents refer to the same point in time in a given survey year. Some larger organisations have a Special Arrangement (SA) in place with the ONS to provide their data electronically; these employers have internal systems that extract and return information on all relevant employees as of the survey reference date.

Employers are generally asked to return their data within one or two months. Reminders follow a set timetable each year: three reminders are sent to employers who respond via special arrangements (in June and July), and one reminder is sent to all other employers (in June).

Fieldwork for ASHE is conducted for Great Britain by ONS and for Northern Ireland by the Northern Ireland Statistics and Research Agency (NISRA). Whilst some official estimates produced from the survey data cover the UK (e.g. ONS, 2023b, 2023c), the research-ready dataset made available to us (ONS, 2024a) only covers Great Britain and so all subsequent discussion in this paper refers to Great Britain only.

2.2 Cross-sectional response rate

The target population for ASHE in Great Britain rose from around 24.1 million jobs in 1997 to around 31.4 million in 2023. As noted above, ASHE is based on an issued sample comprising one per cent of these jobs. Completion of ASHE is mandatory under the Statistics of Trade Act 1947, but inevitably not all sampled businesses respond. Analysis of 2004 data by Pont (2007) found that "good data" were collected for 68% of the issued sample (noting that a substantive proportion of the other returned questionnaires related to individuals exempt from the survey, and that some questionnaires were not useable due to insufficient quality). An ONS review of ASHE in 2010 indicated that the anticipated yield for ASHE (based on the latest survey at the time) stood at 63% of employee jobs (ONS, 2010). Our own calculations show that the yield in Great Britain averaged around 63% across the period from 1997 to 2019 (Figure 1); it has averaged only 46% since the onset of the COVID pandemic.

[FIGURE 1 HERE]

In practice, there are limits to the time and resources available to pursue employers to return questionnaires. Pont (2007) reported on the results of two intensive follow-up exercises run in 2003 and 2004. While these exercises managed to yield additional responses, they also revealed that additional chasing is insufficient to persuade a "hardcore" of employers to respond (Pont, 2007: 723). To our knowledge, there are no published figures on the number of employers prosecuted for not responding to ASHE. Information on the completion of ONS business surveys more generally indicates that the ONS Enforcement Unit deals with thousands of cases of non-completion per year, but few of these reach court or result in prosecution. The stated aim of ONS is to encourage and assist employers to comply, rather than penalise, where possible.[1]

2.3 Longitudinal sample retention

Turning to the panel dimension of ASHE, Figure 2 shows the sample retention rate in ASHE across pairs of years from 2004-2005 to 2012/23, where retention is measured as the re-appearance

[1] https://www.ons.gov.uk/aboutus/transparencyandgovernance/freedomofinformationfoi/businesssurveys

in year $t + 1$ of sample members who appeared in the achieved sample in year t. The figure shows, for example, that 77% of sample members from the 2004 achieved sample were present in the 2005 achieved sample. The retention rate fluctuates over time, but averaged around 75% over the period 2004/5 to 2018/19. There was a drop in retention in 2006/7, when only 64% of the 2006 achieved sample also appeared in the 2007 achieved sample; this coincides with cost-saving cuts to the ASHE sample in 2007. Retention has also been lower since the pandemic, averaging around 64%.

[FIGURE 2 HERE]

This attrition has the potential to introduce bias into estimates generated from the continuously-appearing subset of sample members if they are not representative of employees remaining in jobs across the two years. However, the principal focus within ONS is ensuring the cross-sectional representativeness of ASHE. The panel element of the ASHE dataset is a convenient by-product of the survey's sample design, but ONS does not consider ASHE as one of its 'longitudinal' datasets. As such, there appear to be no explicit attempts within ONS' response chasing protocols to reduce longitudinal attrition. Equally, there appear to be no explicit efforts to detect systematic patterns of longitudinal attrition in the sample. This approach differs fundamentally from that of a classic longitudinal survey (e.g. the UK Household Longitudinal Study), where a cohort of original sample members are followed across successive waves and explicit efforts are made to reduce and adjust for longitudinal attrition among these original members.

2.4 Weighting

ONS derive cross-sectional weights and provide these to researchers with the core ASHE dataset. There are two stages in constructing these weights (ONS, 2018). In the first stage, individual cases are assigned a design weight based on whether they belong to: (i) the original questionnaire despatch; (ii) the group that moves jobs between sample selection and questionnaire despatch; (iii) the group that joins the workforce after the original sample selection; or (iv) the group with special arrangements for response (where employers respond electronically). In the second stage, the design-weighted sample is post-stratified to population estimates taken from the UK Labour Force Survey (LFS) across 108 post-strata, based on the cross-classification of:

- occupation (nine groups) – major groups from the 2010 Standard Occupational Classification
- age bands (three groups) – 16 to 21 years, 22 to 49 years and 50 years and over
- sex (two groups) – male and female
- region (two groups) – London and South East, and the rest of the UK.[2]

The resulting weight (variable CALWGHT) allows estimates to be produced from the ASHE data that are notionally representative of the population of UK employees. In addition, a low pay weight (LPCALWGHT) reweights the dataset after excluding employees whose pay is affected by absence during the survey reference period (a filter commonly used by the Low Pay Commission in their analysis of minimum wage employment).

The lack of an explicit focus within ONS on longitudinal attrition in the survey means that longitudinal weights are neither generated nor made available with the dataset. Existing research using ASHE to track jobs or individuals over two consecutive years relies on the cross-sectional

[2] The LFS is itself weighted to population estimates taken from the Census (ONS, 2024d).

weights (e.g. ONS, 2019) or uses unweighted data (e.g. Elsby et al., 2016; Schaefer and Singleton, 2023). , Therefore, these analyses assume, implicitly or explicitly, that sample attrition between consecutive years is ignorable for the purposes of generating unbiased estimates, or that it remains approximately constant over time (e.g. when analysing business cycle patterns).

There is widespread agreement in the research community that survey weights which make the sample more representative of the population should be used when generating descriptive statistics from survey samples that either depart from simple random sampling or which are subject to non-response (see Solon et al., 2015). The value of weights is more debatable when moving beyond descriptive statistics to undertake multivariate analyses designed to estimate causal effects (ibid.). Then decisions need to be taken on a case-by-case basis, because the downsides can sometimes outweigh the upsides. Here, we focus solely on descriptive statistics, since most of the official statistics generated from ASHE are of this type.

3 Data and Methods

3.1 Assessing the representativeness of the annual ASHE cross-sectional samples

As noted earlier, the standard ASHE weighting scheme devised by ONS seeks to ensure that the weighted data are representative of the employee population by occupation, gender, age, and region. However, as the survey is completed by employers, our further investigation into the cross-sectional representativeness of the annual ASHE samples focuses on employer characteristics.

For an initial investigation of whether response rates vary across employer types, we first examine the population of enterprises recorded each year in the Business Structure Database (BSD) (ONS, 2024b; Evans and Welpton, 2009). The BSD is an annual snapshot of the Inter-Departmental Business Register (IDBR), a comprehensive list of UK enterprises maintained by the ONS and used by government for statistical purposes. Employment information on the IDBR is updated periodically from administrative sources, such as HMRC PAYE and VAT records, as well as ONS surveys, such as the annual Business Register and Employment Survey. The BSD snapshot is extracted in March of each year. The BSD provides the best research-ready source of data on the population of employee jobs that also includes reliable unit-level information on the characteristics of the employers providing those jobs.

We use the number of employees recorded for enterprise j in year t in the BSD (N_{jt}) to compute the expected probability that enterprise j from the BSD will appear in the issued sample for ASHE in year t. Since the issued sample for ASHE comprises a 1% simple random sample of employee jobs, this probability $\hat{y}_{jt}$ can be expressed as follows (Upward, 2007)[3]:

$$\hat{y}_{jt} = 1 - 0.99^{N_{jt}} \qquad \text{Eq. 1}$$

We then use the unique ONS enterprise reference number (ENTREF), which is present on both BSD and ASHE, to identify which of the enterprises in each year of the BSD can be linked to one or more job records in the corresponding year of ASHE.[4] This allows us to create a binary variable

[3] $\hat{y}_{jt}$ will be under-estimated in cases where an employee holds more than one job with a given enterprise. However, the degree of any under-estimation is likely to be very small, since we find that such instances account for less than 1% of all jobs in ASHE in a typical year.

[4] We find that a small proportion of the ENTREFs in ASHE (less than 2% in any one year) are not present in the BSD. We judge that the discrepancy probably arises from differences in the timing of ASHE and the BSD annual snapshot. These cases are dropped from our analysis.

y_{jt}, coded as 1 if enterprise j in year t of the BSD actually appears in the achieved sample for ASHE in year t, and 0 otherwise. The rate at which enterprises respond to ASHE, relative to expectations, can therefore be expressed as:

$$\frac{y_{it}}{\hat{y}_{jt}} \qquad \text{Eq. 2}$$

We use OLS to regress this value on a vector $\boldsymbol{x}_{jt}$ of enterprise demographic characteristics (categorical indicators of employer size, region, legal status, industry and firm age) and year fixed effects, γ_t.

$$\frac{y_{jt}}{\hat{y}_{jt}} = \alpha + \boldsymbol{x}'_{jt}\boldsymbol{\beta} + \gamma_t + \varepsilon_{jt} \qquad \text{Eq. 3}$$

In this firm-level regression, if the probability that a firm responds to ASHE is uncorrelated with its demographic characteristics (after accounting for its probability of selection), then we would expect that $\boldsymbol{\beta} = \boldsymbol{0}$.

As discussed later in Section 4 (Results), we reject this null hypothesis, and so construct an adjustment to the ASHE weights that takes account of residual employer-related response biases within each year. We construct the weighting adjustment by applying the ASHE weights and then undertaking a raking procedure (Deville et al., 1993) to compute a year-specific adjustment factor (xs_adj_{it}) for each employee i in year t of the ASHE. This adjustment brings the weighted ASHE sample of employees closer into line with the BSD profile of employees in respect of a set specified employer characteristics that are suggested by the analysis of Equation 3. Raking is a common method of generating weights, involving an iterative process of adjustments to obtain weights that align with marginal population totals across a number of different variables. We use the `-svycal, rake-` command within Stata, with control totals obtained from the BSD, following the approach set out by Valliant and Dever (2018: 59). This generates a new set of weights:

$$wxs_{it} = weight_{it} \times xs\_adj_{it} \qquad \text{Eq. 3}$$

where $weight_{it}$ is either the standard ASHE cross-sectional weight (CALWGHT) or the ASHE low pay weight (LPCALWGHT) and wxs_{it} is the adjusted version of that weight (named CSWEIGHT and LPCSWEIGHT respectively). Each new weight is then scaled so that $\sum_i wxs_{it} = \sum_i weight_{it}$ within each year.

3.2 Assessing the representativeness of the longitudinal ASHE sample

Any assessment of the representativeness of longitudinal ASHE data across some pair of years, say year t and year $t+1$, should focus on response outcomes among the subset of respondents from year t who remain in scope in the second year. An individual will be out of scope for ASHE in year $t+1$ if they are no longer in PAYE employment, perhaps because they have retired, become unemployed, or switched to self-employment.

Ordinarily, one might investigate patterns of longitudinal response by referring to fieldwork data which traces the circumstances in year $t+1$ of all sample members from year t. However, ONS do not make such fieldwork data available. Accordingly, we rely on comparisons with a benchmark dataset: the Longitudinal Annual Population Survey (LAPS) (ONS, 2023a). The Annual Population Survey is a large household survey providing observations on around 110,000 individuals in employee jobs each year. Around half of these respondents derive from the Quarterly Labour

Force Survey, which surveys individuals across five successive quarters. The remaining half derive from the Local Labour Force Survey, which surveys individuals once a year for up to four years. These repeated observations generate two-year, longitudinal APS (LAPS) samples of around 40,000 individuals holding employee jobs in year t, who also have a follow-up observation indicating their employment status 12 months later in year $t+1$. LAPS is the largest such publicly-available dataset for the UK. Sample attrition within LAPS is accounted for through the use of longitudinal weights which use fieldwork outcomes to adjust for observable attrition biases in that dataset (based on a methodology outlined by Clark and Tate, 1999). We use LAPS data for the period 2004-5 to 2021-22, and use the longitudinal weights to ensure that our estimates are longitudinally representative..[5]

Our estimates from LAPS indicate that around 92% of employees in year t also have employee status 12 months later, with this estimate showing a high degree of consistency over time.[6] In a typical year, the rate of sample retention in ASHE is thus around 17 percentage points lower (see Figure 2). This implies that around one in every six employees in ASHE disappears from the sample between year t and year $t+1$ due to sample attrition. This rate also appears to be increasing over time.

We undertake multivariate analyses to compare the correlates of exiting the ASHE sample with the correlates of exiting employee status in the LAPS. First, we run a probit regression to estimate the probability that employee k in year t of LAPS no longer holds employee status in year $t+1$:

$$y_{kt}^{*} = \alpha + \boldsymbol{x}_{kt}'\boldsymbol{\beta} + \gamma_t + \varepsilon_{kt} \qquad \text{Eq. 4}$$

where: $y_k^* > 0$ corresponds to an employee observed in the LAPS in year t who is not in an employee job at *t+1*; $\boldsymbol{x}_{kt,}$ is a vector of employee, job and employer characteristics that are observed in the LAPS for year t, but which are also common to ASHE; and γ_t are year fixed effects.[7]

We use the estimated coefficients from Eq. 4 to generate a predicted probability of exiting employee status ($\hat{p}_{it}$)for each employee i in year t of ASHE. We then run the following OLS regression:

$$\hat{z}_{it}^{*} = z_{it}^{*} - \hat{p}_{it} = \vartheta + \widetilde{\boldsymbol{x}}_{it}'\boldsymbol{\varphi} + \gamma_t + \epsilon_{it} \qquad \text{Eq. 5}$$

where: $z_{it}^* = 1$ corresponds to an employee observed in ASHE in year t who is not in ASHE at $t+1$ ($z_{it}^* = 0$ otherwise) ; $\widetilde{\boldsymbol{x}}_{it}$ is the same vector of employee, job and employer characteristics included in Eq. 4, but here observed in ASHE, and $\hat{z}_{it}^*$ measures the extent to which the probability of employee *i* exiting the ASHE sample between year *t* and year *t+1* (z_{it}^*) deviates from the

[5] Data from the Longitudinal Labour Force Survey (LLFS), which is nested within the LAPS, were available for one further year (2022/23) at the time of writing. However, the LLFS sample is much smaller than that provided by the LAPS, so we prefer to focus on the shorter time period covered by the LAPS.

[6] Across the years 2004/5 to 2021/22, the minimum rate is 90.8%, observed in 2008/9, and the maximum is 92.9%, observed in 2021/22. The 8% who exit employee status comprise around 2% who are self-employed in year $t+1$, a further 2% who are unemployed and 4% who are inactive (e.g. have retired, entered full-time education). The rate estimated from LAPS is similar to that estimated from the UK Household Longitudinal Study (Understanding Society), which yields a rate of 92.5% for the period 2008-9 (wave 1 to wave 2) (authors' calculations using University of Essex Institute for Social and Economic Research et al., 2017).

[7] An underlying assumption that these characteristics are measured in an equivalent way in either survey. There may be reasons to suppose that employees and their employers are differentially well informed on certain factors, but it is difficult to address any such biases.

probability of employee i exiting employee status over the same period ($\hat{p}_{it}$). This regression is weighted using the ASHE cross-sectional weights derived in Section 3.1.

The mean value of $\hat{z}_i^*$ provides an estimate of the average rate of year-to-year sample attrition in ASHE (i.e. the extent to which the rate of sample exit in ASHE from one year to the next exceeds the rate that would be expected if employment exit were the only cause). In the regression model of Eq. 5, the constant term ϑ shows the estimated rate of sample attrition for an employee belonging to the reference category on all elements of $\widetilde{\boldsymbol{x}}_{it}$; the coefficients in $\boldsymbol{\varphi}$ show the extent to which that rate of sample attrition varies across the elements of $\widetilde{\boldsymbol{x}}_{it}$, on average over the sample period. If $\boldsymbol{\varphi} \neq 0$, then this implies that the pattern of sample exit in ASHE differs systematically from the pattern of employment exit in APS over the sample period. Individual coefficients in $\boldsymbol{\varphi}$ then indicate which factors in $\widetilde{\boldsymbol{x}}_{it}$ marginally predict this different sample exit probability, conditional on what all the APS factors in $\boldsymbol{x}_{it}$ and the forecasting model predict, $\hat{p}_{it}$. Such outcomes indicate the presence of general and specific attrition biases in the year-to-year (two-year) longitudinal ASHE samples. This approach is broadly equivalent to the popular Mincer and Zarnowitz (1969) forecast evaluation framework, in which one seeks to identify the characteristics associated with the bias or efficiency of forecasts.[8]

To address the attrition biases, we construct a set of two-period longitudinal weights for each year of ASHE. We run an equivalent probit regression to that shown in Eq. 4 within each year of ASHE to generate the predicted probability ($\hat{q}_{it}$) that each employee i in ASHE will exit the sample between year t and year $t+1$. Generating $\hat{p}_{it}$ and $\hat{q}_{it}$ separately for each year t allows for time-variance in the correlates of employment exit and sample exit. A year-specific 'attrition adjustment factor' (att_adj_{it}) is then constructed for each employee i in year t who survives in the ASHE sample to year $t+1$:

$$att\_adj_{it} = \frac{1}{(1-\hat{q}_{it})} \times (1-\hat{p}_{it}) \qquad \text{Eq. 6}$$

The first term boosts the representation in the two-period sample of those most likely to exit ASHE between year t and $t+1$ (restoring the profile of the two-period sample to that of the full sample in year t). The second term then calibrates this adjustment to account for each individual's probability of exiting employment exit between year t and $t+1$ (reducing the size of the adjustment factor in proportion to the individual's likelihood of moving out of scope).[9] A final two-period longitudinal weight ($watt_{it}$) is then constructed for each ASHE individual i in year t who survives in the sample to year $t+1$ as:

$$watt_{it} = wxs_{it} \times att\_adj_{it} \qquad \text{Eq. 7}$$

[8] If both models were linear, this approach would be equivalent to running separate regressions of y_i^* and z_i^* and then comparing the equality of equivalent coefficients across the regressions (which could itself be achieved by pooling the LAPS and ASHE data and running a stacked regression in which all the variables in $\boldsymbol{x}$ are interacted with a dummy variable identifying the ASHE sample members).

[9] The formula may also be reconfigured as $\hat{p}(emp\_stay)/\hat{p}(samp\_stay)$, i.e. the ratio of expected 'stayers' to observed 'stayers'. This helps to indicate that the largest adjustments will be for those cases where the probability of staying in the observed sample is much lower than the true rate of remaining in PAYE employment.

where wxs_{it} is the ASHE cross-sectional weight generated for individual i in year t via the procedure outlined in Section 3.2.[10] We name these new weights CSWATT and CSWATTLP. The new weights are scaled so that $\sum_i watt_{it} = \sum_i wxs_{it}$ within each year.

We restrict our attention to longitudinal attrition across consecutive pairs of years $(t, t+1)$, rather than studying longer time-periods, because most longitudinal analyses of ASHE focus on year-to-year changes in hours, earnings or employment (see for example, ONS, 2019). It also becomes more challenging to obtain benchmark estimates for the probability of exiting employee status $(\hat{p}_{it})$ when the follow-up period extends beyond one year.[11]

4 Results

4.1 Representativeness of annual ASHE cross-sections

Table 1 presents the results of estimating Eq. 3 in Section 3.1 using the BSD. Some patterns of systematic non-response are apparent in the table, particularly in respect of employer size and legal status. The response rate among the largest firms is around 50 percentage points higher than among the smallest firms *cet. par.*; organisations in central government are around 15 percentage points more likely to respond than private limited companies *cet. par.*

[TABLE 1 HERE]

Table 2 compares the profile of employment in ASHE with that observed in the population of enterprises as captured by the BSD. Estimates are presented for 2023, as a representative example of the situation throughout the whole series. In contrast to the statistics in Table 1, this analysis utilises the existing ASHE weights. This is important as they may reduce any employer-related responses biases in the unweighted sample through any correlations between employer characteristics and the occupation, gender, age, and regional distribution of employment. Column 1 shows the percentages of employee jobs in each category as observed in the BSD; column 2 shows the equivalent percentages in ASHE after applying the standard ASHE weights (CALWGHT).[12] Column 3 shows the differences between the ASHE weighted estimates and the BSD estimates, which can be interpreted as a measure of the bias in the ASHE estimates generated under the standard weighting scheme, assuming that the estimates generated from the BSD are unbiased. The figures in Column 3 indicate that employee jobs in larger firms are over-represented in the ASHE sample, even after applying the standard ASHE weights. Jobs in private sector enterprises (especially companies) and younger enterprises are under-represented, while those in public sector enterprises and older enterprises are over-represented.

[TABLE 2 HERE]

The rows of Column 4 in Table 2 show the squared value of the bias for each category of each variable, which is then averaged over all categories of the variable at the base of each set of values. This averaged value allows us to estimate the extent of bias across variables with different numbers of categories; larger values indicate that the profile of ASHE is more biased across that particular

[10] The attrition weight therefore incorporates our adjustment for non-response bias in year t.

[11] A subset of respondents to the Annual Population Survey are followed-up over 5 years, but this sample is very small. The UK Household Longitudinal Study has followed individuals each year since 2009, but the sample is not refreshed annually in order to remain cross-sectionally representative, and so the survey would only provide estimates of the probability of employment exit over a period $(t, t+k)$ when t = 2009.

[12] Strictly speaking, figures for the BSD show the percentage of employees rather than employee jobs, but as noted earlier, the percentage of employees holding multiple jobs with the same employer is very small.

variable. The largest values are seen in respect of workforce size, legal status and firm age.[13] While there are some differences between the BSD and ASHE in terms of the distribution of jobs across region and industry (jobs in Education and Health and Social Work are over-represented in ASHE compared to the profile observed in the BSD, for example), the magnitude of the bias is relatively small across these dimensions.

As described in Section 3.1, we use a raking procedure to adjust the standard ASHE weights, aiming to account for residual employer-related response biases. It is important to be relatively parsimonious in the variables used for this adjustment. While a greater number of variables (and categories) will reduce any sample bias, it may also introduce additional variability into the weighting scheme, thereby reducing the precision of estimates generated using the new weights (Kish, 1992). Informed by the analysis presented in Table 1 and Table 2, we focus on three variables for our adjustment: employer size (1-4 employees; 5-49 employees; 50-4,999 employees; 5,000 or more employees); legal status (private sector; public sector; non-profit); and firm age (less than 10 years old; 10-29 years; 30 or more years). We also trim the weights following the approach recommended by Valliant and Dever (2018: 157), capping the maximum and minimum weight values at points equal to the median value of the weight plus or minus three times the value of the interquartile range.

Table 3 compares the performance of this new adjusted ASHE weight (CSWEIGHT) with that of the original weight (CALWGHT). The adjusted weight delivers a reduction in bias compared to the original ASHE weighting on all dimensions considered. The Kish (1965) design effect, which provides a measure of the variability of the original and adjusted weights, shows that the adjusted weighting scheme incurs only a small loss of precision.

[TABLE 3 HERE]

To check that our adjusted weight does not inadvertently distort the weighted profile of ASHE based on employee characteristics (especially those targeted under the original weighting scheme), Supplementary Appendix Table A2 compares the ASHE sample profiles under the original and our adjusted weights for key employee characteristics. We see that the weighted profiles by employee characteristics are very similar under both weighting schemes.

Table 4 illustrates the impact of the weighting adjustment on descriptive statistics for nominal gross hourly earnings for selected years of ASHE (2004, 2013 and 2023, representing the beginning, middle and end of the current data series). The main effect of the weighting adjustment is a leftward shift in the hourly earnings distribution each year. Mean gross hourly earnings are lower by 17 pence per hour in 2004 ($t=3.87$; $p<0.001$), 38 pence per hour in 2013 ($t=4.48$; $p<0.001$), and 44 pence per hour in 2023 ($t=6.23$; $p<0.001$). The impact is greater in the upper half of the distribution, and so the interquartile range (IQR) becomes narrower in absolute terms each year under CSWEIGHT, with the effect of the weighting adjustment being greater in later years. Wage inequality – measured by the IQR – is therefore lower under the new weighting scheme, although the impact on the p90: p10 ratio – another measure of inequality – is minimal. The final columns of Table 4 show the growth in nominal wages across the whole period (2004 to 2023). Growth in mean nominal wages is slightly lower under the new weights but the difference

13 In interpreting these findings, one must bear in mind that the values in Table 2 focus on one variable at a time. Firm age is correlated with size and legal status, and hence the particularly pronounced differences by age seen in Table 2 are likely to be partly accounted for by size and legal status in the regression analysis presented in Table 1.

is very small (70% versus 69%). The leftward adjustment to the distribution is thus proportionately similar across years.

[TABLE 4 HERE]

4.2 *Representativeness of the two-period longitudinal ASHE sample*

To examine the representativeness of the longitudinal samples of employees observed in year t and year $t+1$, we estimate the regression model specified in Equation 5. Table 5 presents the results, showing statistically significant differences in attrition rates across all characteristics. In particular, younger employees (except those aged 16-19), those living in London, those with higher pay and those with low tenure are shown to be less likely to reappear in ASHE in year $t+1$, conditional on having appeared in year t, and after accounting for their probability of remaining in scope (i.e. continuing to have employee status).[14]

[TABLE 5 HERE]

The effect of these differential patterns of sample exit will be to skew the two-period longitudinal sample in ASHE away from the profile that would be expected on the basis of employment exit alone. In respect of tenure, for example, we could expect the sample to have an under-representation of low-tenured employees, due to the uneven effects of sample attrition. We use the steps outlined in Section 3.2 to construct a year-specific two-period longitudinal weight ($watt_{it}$) for each ASHE individual i who is observed as an employee in year t and survives in the sample to year $t+1$ (i.e., is observed again as an employee). Table 6 illustrates the impact of the new weights by presenting the profile of the two-period sample for ASHE 2021-22 under the cross-sectional weight (CSWEIGHT), which has no adjustment for attrition, and the new longitudinal weight (WATT). The new weight induces small shifts in favour of younger workers, those in London, and those with low tenure. The reduction in bias comes with a small loss of precision, as the estimated Kish design effect rises from 1.21 to 1.25.

[TABLE 6 HERE]

Table 7 illustrates the impact of the longitudinal weights on estimates of annual, within-person growth in nominal gross hourly earnings, again for selected years of ASHE. The longitudinal weights slightly shift the distribution of growth to the right and induce a small widening of the distribution, likely due to increased representation of younger workers. The impacts are most evident in 2021/22, when the increase of 0.57 percentage points in the mean is statistically significant from zero (t=3.35; p<0.001) and the IQR increases by 0.48 percentage points. In the spirit of Elsby et al (2019) and others, we generate estimates of the share of employees experiencing nominal wage cuts, wage rigidity, and wage growth. The share of employees experiencing wage growth increases marginally by 0.56 percentage points (t=2.31; p<0.05).

[TABLE 7 HERE]

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[14] APS and ASHE do each contain additional, unique characteristics that are likely associated with employment exit and sample exit respectively. However, they cannot be employed here as they are not common to both datasets. We estimated models that included such characteristics, but the additional variance explained in each dataset was small.

5 Implications for estimates of the incidence of low pay

We use the new weights to assess the implications of sample bias in ASHE for estimates of low pay. Improving estimates of the incidence of low pay was a key motivation for the introduction of ASHE, and it remains the primary data source used by the Low Pay Commission, ONS, and others to estimate patterns of pay and the impact of minimum wage legislation (Low Pay Commission, 2022, ONS, 2023c, Cominetti et al., 2022).

First, we investigate the coverage rate of the minimum wage under the alternative weighting schemes. This is a key benchmark as it indicates the share of all jobs that are paid at the wage floor. It indicates the reach of the minimum wage across the labour market and how this changes as the minimum wage is uprated.

Second, we investigate the bite of the minimum wage, which is the value of the minimum as a percentage of median wages, also knows as the Kaitz Index. Since the introduction of ASHE in 2004, the UK Government has progressively increased the bite of the National Minimum Wage (NMW). In 2016, the Government also introduced a higher National Living Wage (NLW) for employees aged 25 and over, with eligibility subsequently extended to employees aged 23-24 in 2021 and those aged 21-22 in 2024. When the NLW was introduced, the Government set a target for it to reach 60 percent of median hourly earnings by October 2020, and subsequently revised the target to two-thirds of median hourly earnings by October 2024 (DBEIS, 2020). We assess progress towards this target.

Third, we investigate rates at which workers move off the minimum wage. This metric is expected to become increasingly important as the coverage and bite of the minimum wage increase. Greater compression at the lower end of the wage distribution could raise concerns about whether minimum wage workers have fewer opportunities for wage progression (Low Pay Commission, 2022; Forth et al., 2024).

In Section 4, we found that our adjusted cross-sectional weights shifted the cross-sectional wage distribution to the left. As a result, we would expect the coverage rate and bite of the minimum wage to be higher under our adjusted weight compared to the standard ASHE weights. Similarly, Section 4 showed that our new longitudinal weights slightly shifted the distribution of wage growth to the right. Therefore, we might expect a modest increase in the rate at which people exit the minimum wage, especially in later years.

5.1 The coverage rate and bite of the National Minimum Wage and National Living Wage

Using the cross-sectional low-pay weights supplied by ONS (LPCALWGHT), the share of jobs paid at or below the NMW or NLW rose from 2.7% in 2004 to 4.3% in 2015 (Figure 3).[15] The introduction of the NLW in 2016 pushed the incidence further upwards, reaching 6.7%. The coverage rate declined slowly through to 2019, after which it fell more rapidly, reaching 4.9% in 2023. Applying our adjusted cross-sectional weights (LPCSWEIGHT) raises the estimated share

[15] We follow the Low Pay Commission (LPC) in using a measure of gross hourly earnings that includes basic pay, bonus or incentive pay, and pay received for other reasons but excludes overtime and shift premium pay. We also follow the LPC in measuring the employee's wage against the NMW or NLW rate that applied in April of the relevant year, even if (from 2016 onwards) the NLW may have been uprated part-way through the pay period reported in ASHE. And we follow the LPC in measuring the share of jobs paid at or below the NMW and NLW plus 5 pence. Our estimates for 2020 and 2021 make no attempt to adjust the wages of employees on furlough, however, and so are lower than those reported by the LPC who make adjustments which raise the pay of such employees to arrive at an estimate of what the employee would be paid if they were not furloughed.

of jobs paid at or below the NMW or NLW by approximately one fifth in each year. This raises the share to 8.1% in 2016 and 6.3% in 2023. The differences between the estimates from the two sets of weights are statistically significant from zero in every year of the series.

[FIGURE 3 HERE]

Regarding the bite of the NMW and NLW, the original ASHE cross-sectional weights estimate it to have risen from 51.4% in 2004 to 64.1% in 2023 (Figure 4). According to these estimates, the UK Government appeared to meet its target of a 60% bite in 2020. However, when the median wage is instead estimated using our adjusted cross-section weights, the bite is found to have risen from 52.7% in 2004 to 66.7% in 2023. The revised estimates show that the 60% target was reached in 2018 – two years earlier than previously thought – and the target of two-thirds median wages was met by 2023 – one year ahead of schedule.

[FIGURE 4 HERE]

5.2 The probability of escaping the National Minimum Wage or National Living Wage

Using a balanced panel of employees who appear as employees in ASHE in adjacent years, we estimate the share of minimum wage workers in each year who transition to a better paid job 12 months later. Using our adjusted cross-sectional low pay weight (LPCSWEIGHT), which includes no adjustment for panel attrition, we find that the rate of escape fell from 57.6% in 2004-2005 to 29.9% in 2015-2016, before increasing back to a rate of 55.2% in 2021-2022 (Figure 5).[16] Switching to our new longitudinal weighting scheme in fact brings only marginal differences across the series. The largest differences occur in 2014-2015 and 2015-2016 (0.7 percentage points), 2019-2020 (1.1 percentage points), and 2021-2022 (0.8 percentage points), but the differences are not statistically significant from zero in any year of the series.

[FIGURE 5 HERE]

The situation is very similar when estimating the probability of a minimum wage worker escaping the wage floor by at least £1 per hour. With our adjusted cross-sectional weights, the rate of escape fell from 34.2% in 2004-2005 to 14.9% in 2015-2016, before increasing back to a rate of 27.4% in 2021-2022 (Figure 6). With our new longitudinal weights, estimates are typically around 0.5 percentage points higher from 2013-2014 onward but, again, the differences are not statistically significant from zero in any year.

[FIGURE 6 HERE]

6 Summary and conclusions

The Annual Survey of Hours and Earnings (ASHE) provides many of the UK's official earnings statistics, based on an issued sample comprising 1% of all employee jobs. Its predecessor, the NES, was criticised for lacking survey weights to address known response biases. ASHE improved upon this by introducing cross-sectional weights that adjust the profile of the achieved annual samples to ensure they are representative of the population of employee jobs in terms of gender, age, occupation, and region (see Bird, 2004; Pont, 2007).

[16] Estimates for 2019-20, 2020-21 and 2021-22 are necessarily affected by the introduction and cessation of furlough. See also footnote 15.

The analysis presented in this paper reveals that jobs in smaller, younger, and private-sector enterprises remain under-represented in the annual achieved samples, even after applying those weights. We develop an alternative set of cross-section weights aimed at reducing these biases. Our findings indicate that the incidence of minimum wage employment is under-estimated under the original cross-sectional weighting scheme. Our new weights also suggest that that the bite of the minimum wage is higher, and that government targets for the bite have been reached earlier than previously estimated.

We also identify systematic patterns of longitudinal attrition in ASHE, for which there are no official weighting adjustments. After accounting for an employee's probability of remaining in scope for the survey, we find that male employees, younger and middle-aged employees, and those with low tenure are less likely to reappear in ASHE in the following year. Although the impact of these differential rates of attrition on the composition of the longitudinal sample is relatively small, we develop a set of longitudinal weights to address this issue. These revised weights marginally increase the estimated share of workers who escape from the minimum wage by the following year, but the differences are not large enough to be statistically significant.

Our findings contribute to the literature on rates and patterns of minimum wage employment and low pay in the UK (e.g. Dickens et al., 2015; Aitken et al., 2019; Low Pay Commission, 2022). They also contribute to the broader literature on the nature, detection and removal of non-response biases in business surveys (e.g. Willimack et al., 2002; Willimack and Snijkers, 2013), highlighting the value of revisiting the non-response processes and the benefits of using multiple auxiliary sources for calibration.

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Table 1: Probability that a BSD employer appears in ASHE relative to expectations, OLS regression results

	Coefficient		Std. error
Employer size (ref. 1-4 employees)			
1-4	0.153	***	0.002
5-9	0.259	***	0.002
50-249	0.326	***	0.003
250-499	0.416	***	0.004
500-999	0.475	***	0.005
1000-2499	0.515	***	0.006
2500-4999	0.529	***	0.008
5000 plus	0.519	***	0.011
Region (ref. London)			
North East	0.030	***	0.006
North West	-0.009	***	0.003
Yorkshire & Humberside	0.015	***	0.004
East Midlands	0.014	***	0.004
West Midlands	-0.001		0.003
South West	0.011	***	0.003
East	-0.038	***	0.002
South East	0.023	***	0.003
Wales	0.009	*	0.005
Scotland	0.009	**	0.004
Legal status (ref. Private company)			
Sole proprietor	0.065	***	0.003
Partnership	0.071	***	0.005
Public corporation	0.084	**	0.039
Central government body	0.191	***	0.016
Local authority	0.248	***	0.028
Non-profit making body	0.124	***	0.007
Industry (SIC07) (ref. Manufacturing)			
Agriculture, forestry, fishing	-0.069	***	0.008
Mining and quarrying	-0.075	***	0.020
Electricity, gas	-0.111	***	0.008
Water supply	-0.018	*	0.010
Construction	-0.031	***	0.004
Wholesale, retail	-0.009	**	0.004
Transport and storage	-0.039	***	0.004
Accommodation & food	-0.055	***	0.004
Information & communication	-0.038	***	0.004
Financial and insurance	0.026	***	0.007
Real estate	-0.053	***	0.005
Professional, scientific, technical	-0.025	***	0.004

Admin and support	-0.030	***	0.004
Public administration	0.190	***	0.046
Education	0.046	***	0.006
Health and social work	0.069	***	0.006
Art, entertainment, recreation	-0.027	***	0.006
Other service activities	0.060	***	0.006
Firm age (ref. 1 year or less)			
2-4 years	-0.010	***	0.002
5-9 years	-0.006	***	0.002
10-19 years	0.042	***	0.002
20-29 years	0.091	***	0.003
30+ years	0.116	***	0.004
Year (ref. 2004)			
2005	0.000		0.002
2006	-0.033	***	0.002
2007	-0.077	***	0.003
2008	-0.091	***	0.003
2009	-0.081	***	0.003
2010	-0.080	***	0.003
2011	0.004		0.003
2012	-0.031	***	0.003
2013	-0.037	***	0.003
2014	-0.027	***	0.003
2015	-0.011	***	0.003
2016	-0.022	***	0.003
2017	-0.032	***	0.003
2018	-0.011	***	0.003
2019	-0.036	***	0.003
2020	-0.055	***	0.003
2021	-0.060	***	0.003
2022	-0.067	***	0.003
2023	-0.078	***	0.003
Constant	0.177	***	0.005
N observations(enterprises)	*54,292,380*		
R-squared	*0.002*		

Base: all enterprises with at least 1 employee, located in England, Scotland or Wales.
Notes: author calculations using BSD dataset. See Equation (3.) ***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively. Robust standard errors.

Table 2: Employer characteristics associated with response to ASHE, 2023

	BSD (employee-weighted), per cent	ASHE weighted (CALWGHT), per cent	Bias in ASHE (2)- (1)	Bias squared
	(1)	(2)	(3)	(4)
Number of employees:				
1-4	11.8	4.2	-7.7	58.9
5-9	6.2	4.2	-2.0	4.1
10-49	15.5	14.6	-0.9	0.8
50-249	14.1	15.1	1.1	1.1
250-499	5.8	6.5	0.7	0.5
500-999	6.0	7.3	1.3	1.6
1000-2499	7.2	8.3	1.0	1.1
2500-4999	6.8	8.3	1.4	2.0
5000 plus	26.5	31.6	5.1	25.8
Average bias (mean):				*10.7*
Legal status:				
Company	72.9	64.5	-8.4	69.8
Sole proprietor	2.1	1.2	-1.0	0.9
Partnership	1.9	2.0	0.1	0.0
Public corporation	0.7	0.8	0.1	0.0
Central government body	9.9	14.2	4.2	18.1
Local authority	5.9	8.6	2.7	7.3
Non-profit making body	6.6	8.8	2.2	4.8
Average bias (mean):				*14.4*
Age of firm:				
1 year or less	2.2	0.7	-1.4	2.1
2-4 years	8.5	3.3	-5.2	27.1
5-9 years	10.7	6.3	-4.4	19.8
10-19 years	14.2	11.7	-2.5	6.5
20-29 years	13.3	14.3	0.9	0.9
30 years plus	51.1	63.8	12.7	161.0
Average bias (mean):				*36.2*
Workplace location:				
North East	3.6	3.6	0.0	0.0
North West	10.1	9.9	-0.2	0.1
Yorkshire	7.7	8.0	0.3	0.1
East Midlands	7.2	7.1	0.0	0.0
West Midlands	8.5	8.2	-0.3	0.1
South West	9.9	10.5	0.6	0.3

East	21.3	18.2	-3.2	10.0
London	13.7	15.0	1.2	1.5
South East	7.5	8.4	0.9	0.8
Wales	3.5	3.7	0.2	0.0
Scotland	7.0	7.5	0.5	0.3
Average bias (mean):				*1.2*
Industry (SIC(2007) Section):				
Agriculture, forestry, and fishing	1.0	0.6	-0.4	0.2
Mining and quarrying	0.2	0.1	-0.1	0.0
Manufacturing	7.5	8.9	1.5	2.2
Electricity, gas, air cond. supply	0.4	0.4	0.0	0.0
Water supply, sewerage, waste	0.6	0.7	0.1	0.0
Construction	5.1	3.7	-1.4	1.9
Wholesale, retail, repair of vehicles	14.6	13.9	-0.7	0.4
Transport and storage	4.6	3.9	-0.6	0.4
Accommodation and food service	8.0	5.4	-2.6	6.7
Information and communication	4.5	4.3	-0.3	0.1
Financial and insurance activities	3.3	3.8	0.5	0.3
Real estate activities	2.0	1.6	-0.5	0.2
Professional, scientific, and technical	8.3	8.0	-0.4	0.1
Admin and support services	9.4	6.3	-3.1	9.4
Public admin and defence	3.7	5.3	1.5	2.3
Education	9.7	13.9	4.2	17.3
Health and social work	12.8	15.5	2.7	7.2
Art, entertainment, and recreation	2.2	1.9	-0.3	0.1
Other service activities	1.9	1.7	-0.2	0.0
Activities of households as employers	0.1	0.1	-0.1	0.0
Average bias (mean):				*2.4*
N observations	*3,127,074*	*148,573*		

Base: all employee jobs.

Note: Figures for BSD are employee-weighted estimates, for those enterprises that are recorded as having at least one employee in the BSD. ASHE estimates exclude those employee jobs for whom it was not possible to match to an enterprise record in BSD (affecting 0.5 per cent of the original ASHE sample in 2023).

Table 3: Bias and design effect, original and adjusted ASHE weights, 2023

	Original ASHE weight (CALWGHT)	Adjusted ASHE weight (CSWEIGHT)
Average bias - size	10.7	1.5
Average bias - status	14.4	0.3
Average bias - age	36.2	2.5
Average bias - region	1.2	1.0
Average bias - industry	2.4	0.6
Average bias (all)	9.0	1.0
Kish design effect	1.15	1.29

Base: all employee jobs.

Notes: author calculations using ASHE dataset, 2023. Number of observations: 148,573.

Table 4: Employee nominal gross hourly earnings (pence per hour) under different weighting schemes, 2004, 2013 and 2023

	2004			2013			2023			Growth (2023/2004)		
	CALWGHT	CSWEIGHT	Diff.	CALWGHT	CSWEIGHT	Diff.	CALWGHT	CSWEIGHT	Diff.	CALWGHT	CSWEIGHT	Diff.
Mean	1145	1128	-17	1461	1423	-38	1950	1906	-44	1.70	1.69	-0.01
p10	505	500	-5	653	645	-8	1069	1051	-18	2.12	2.10	-0.01
p25	623	611	-13	800	774	-26	1196	1171	-25	1.92	1.92	0.00
p50	887	864	-22	1132	1094	-39	1565	1505	-60	1.76	1.74	-0.02
p75	1374	1338	-35	1744	1683	-61	2290	2220	-70	1.67	1.66	-0.01
p90	2018	1993	-25	2530	2481	-49	3235	3189	-46	1.60	1.60	0.00
IQR	750	728	-23	944	909	-36	1094	1050	-44	1.46	1.44	-0.02
p90/p10	3.99	3.99	-0.01	3.88	3.85	-0.03	3.03	3.03	0.01	0.76	0.76	0.00
Num. obs.	*147,138*	*147,138*		*168,934*	*168,934*		*138,162*	*138,162*				

Base: all employee jobs paid on adult rates, where no loss of pay due to absence.
Notes: author calculations using ASHE dataset. Diff. = Difference (CSWEIGHT – CALWGHT), pence per hour. IQR = interquartile range (p75-p25). Growth = (Estimate_{2023}/Estimate_{2004}). The measure of gross hourly earnings includes basic pay, bonus or incentive pay and pay received for other reasons, but excludes overtime and shift premium pay (ASHE variable: HRPAYX)

Table 5: OLS regression to estimate patterns of two-period sample attrition in ASHE, 2004/5-2021/22, relative to an employee's probability of moving out of scope, estimated from LAPS

	Coefficient		Std. error
Gender (Ref. Female):			
Male	0.015	***	0.001
Age group (Ref: 16-19 years)			
20-24	0.062	***	0.002
25-29	0.064	***	0.002
30-34	0.056	***	0.002
35-39	0.043	***	0.002
40-44	0.032	***	0.002
45-49	0.026	***	0.002
50-54	0.017	***	0.002
55-59	0.008	***	0.002
60-64	-0.015	***	0.002
65+	-0.055	***	0.003
Occupation (ref: Managers, directors and senior officials)			
Science, research, engineering and tech	-0.011	***	0.001
Associate professional and technical	0.001		0.001
Administrative and secretarial	-0.028	***	0.001
Skilled trades occupations	-0.001		0.002
Caring, leisure and other service occupation	-0.011	***	0.002
Sales and customer service occupations	-0.037	***	0.002
Process, plant and machine operatives	-0.008	***	0.002
Elementary occupations	-0.024	***	0.002
Industry (ref: Sections A-E)			
F: Construction	0.010	***	0.002
G: Wholesale, retail, repair of vehicles	0.001		0.001
H; Transport, and storage	-0.009	***	0.001
I; Accommodation, and food service	0.064	***	0.002
J; Information, and communication	0.042	***	0.002
K: Financial and insurance activities	-0.003	*	0.002
L: Real estate activities	0.027	***	0.004
M: Professional, scientific, and technical	0.026	***	0.001
N: Admin and support services	0.060	***	0.002
O: Public admin and defence	0.010	***	0.002
P: Education	-0.001		0.001
Q: Health, and social work	0.008	***	0.002
R: Art, entertainment, and recreation	0.018	***	0.002
S: Other service activities	-0.007	**	0.003
Region of workplace (Ref: North East)			
North West	0.008	***	0.002

Yorkshire and Humberside	-0.004	*	0.002
East Midlands	0.002		0.002
West Midlands	0.004	**	0.002
South West	-0.003		0.002
East of England	0.006	***	0.002
London	0.049	***	0.002
South East	0.014	***	0.002
Wales	-0.007	***	0.002
Scotland	-0.004	*	0.002
Sector of ownership (Ref. Private):			
Public	-0.029	***	0.001
Decile of real gross hourly pay (Ref: the lowest)			
2nd decile	-0.035	***	0.001
3rd decile	-0.040	***	0.001
4th decile	-0.039	***	0.002
5th decile	-0.046	***	0.002
6th decile	-0.055	***	0.002
7th decile	-0.060	***	0.002
8th decile	-0.061	***	0.002
9th decile	-0.059	***	0.002
10th decile	-0.051	***	0.002
Basic working hours (Ref: <=15)			
16-29	-0.018	***	0.001
30-47	-0.016	***	0.001
48 plus	0.000		0.003
Tenure (Ref: <1 year)			
1-2 years	-0.026	***	0.001
2-5 years	-0.054	***	0.001
5-9 years	-0.081	***	0.001
10-20 years	-0.094	***	0.001
20 years or more	-0.095	***	0.001
Missing/invalid	-0.026	***	0.002
Workplace size (Ref: 1-24 employees)			
25-49	-0.011	***	0.002
50-499	0.004	***	0.001
500+	-0.013	***	0.001
Missing	0.093	***	0.010
Year (Ref: 2004)			
2005	-0.009	***	0.002
2006	0.129	***	0.002
2007	0.016	***	0.002
2008	-0.014	***	0.002
2009	0.006	***	0.002
2010	-0.007	***	0.002

2011	0.021	***	0.002
2012	0.005	***	0.002
2013	0.005	***	0.002
2014	0.030	***	0.002
2015	0.041	***	0.002
2016	0.036	***	0.002
2017	0.039	***	0.002
2018	0.053	***	0.002
2019	0.177	***	0.002
2020	0.115	***	0.002
2021	0.137	***	0.002
Constant	0.238	***	0.003
Observations	*2,939,373*		
R-squared	*0.040*		

Base: all employee jobs.

Notes: author calculations using ASHE and LAPS datasets. See Equation (5.) ***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively. Robust standard errors.

Table 6: The profile in 2021 of the ASHE two-period sample using cross-sectional and longitudinal weights (cell proportions), 2021-2022

Sample	Observed in Year t and $t+1$	Observed in Year t and $t+1$	Difference (2)-(1)
Weights	Cross-sectional (CSWEIGHT)	Longitudinal (WATT)	
	(1)	(2)	(3)
Gender:			
Female	48.8	48.9	0.1
Male	51.2	51.1	-0.1
Age group:			
16-19	2.3	2.5	0.1
20-24	7.4	8.2	0.9
25-29	10.9	11.7	0.9
30-34	12.4	12.9	0.6
35-39	11.9	12.2	0.2
40-44	11.6	11.5	-0.1
45-49	12.1	11.6	-0.5
50-54	12.1	11.4	-0.7
55-59	10.4	9.8	-0.6
60-64	6.3	5.9	-0.4
65+	2.6	2.3	-0.3
Occupation:			
Managers, directors and senior officials	11.3	11.0	-0.3
Science, research, engineering and tech	22.0	21.7	-0.3
Associate professional and technical	14.8	14.9	0.1
Administrative and secretarial	12.5	11.9	-0.6
Skilled trades occupations	7.1	7.2	0.1
Caring, leisure and other service occupation	8.9	9.3	0.4
Sales and customer service occupations	8.6	8.3	-0.3
Process, plant and machine operatives	5.1	5.2	0.0
Elementary occupations	9.6	10.5	0.9
Industry:			
A-E: Agriculture, Mining, Manufacturing, Energy & Water	12.5	12.0	-0.5
F: Construction	4.8	4.7	0.0
G: Wholesale, retail, repair of vehicles	17.0	16.6	-0.4
H; Transport, and storage	4.5	4.5	0.0
I; Accommodation, and food service	4.5	5.3	0.8
J; Information, and communication	3.6	3.7	0.1
K: Financial and insurance activities	4.2	3.9	-0.3
L: Real estate activities	1.5	1.6	0.1
M: Professional, scientific, and technical	8.0	8.5	0.5
N: Admin and support services	5.3	6.0	0.7

O: Public admin and defence	4.6	4.1	-0.5
P: Education	12.0	11.6	-0.4
Q: Health, and social work	13.8	13.7	-0.2
R: Art, entertainment, and recreation	1.5	1.5	0.0
S: Other service activities	2.2	2.2	0.0
Region of workplace:			
North East	3.6	3.6	-0.1
North West	10.7	11.0	0.3
Yorkshire and Humberside	8.5	8.2	-0.3
East Midlands	7.4	7.3	-0.1
West Midlands	9.0	8.7	-0.3
South West	9.0	8.8	-0.1
East of England	9.4	9.3	-0.1
London	13.7	14.8	1.2
South East	15.3	15.6	0.3
Wales	4.6	4.4	-0.2
Scotland	8.8	8.2	-0.6
Sector of ownership:			
Private	80.5	81.7	1.1
Public	19.5	18.3	-1.1
Decile of real gross hourly pay:			
1st decile	8.2	9.5	1.3
2nd decile	8.4	8.8	0.4
3rd decile	8.6	8.7	0.1
4th decile	8.6	8.8	0.2
5th decile	9.4	9.4	0.0
6th decile	10.1	9.5	-0.5
7th decile	10.8	10.3	-0.4
8th decile	11.3	11.0	-0.4
9th decile	12.0	11.5	-0.5
10th decile	12.6	12.4	-0.2
Basic working hours:			
1-15	9.4	10.2	0.7
16-29	17.3	17.3	0.0
30-47	71.4	70.4	-1.0
48 plus	1.9	2.1	0.2
Tenure:			
Less than 1 year	12.1	13.9	1.9
1-2 years	12.9	14.2	1.3
2-5 years	25.7	26.4	0.7
5-9 years	19.8	19.0	-0.8
10-20 years	18.1	16.3	-1.8
20 years or more	9.4	8.1	-1.3
Missing/invalid	1.9	2.1	0.1

Workplace size:			
1-24 employees	21.7	21.8	0.1
25-49	7.2	7.3	0.1
50-499	21.2	21.7	0.5
500+	50.0	49.3	-0.7
Kish design effect	1.21	1.25	
Observations	*85,398*	*85,398*	

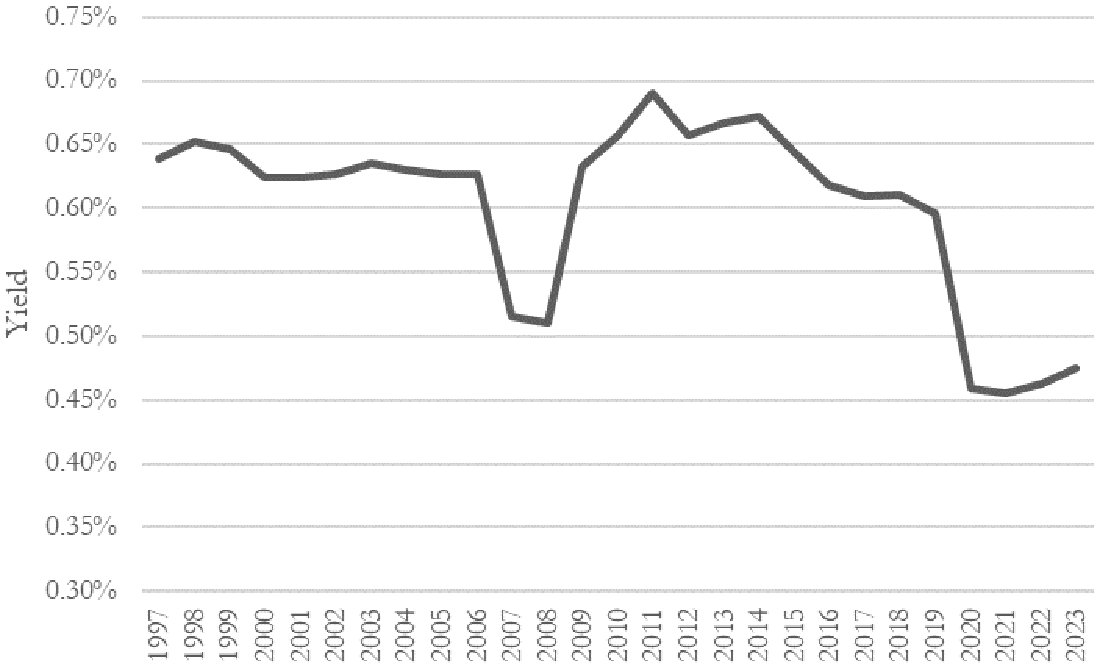
Base: jobs held by employees who retain employee status from year *t* to year *t+1*.
Notes: author calculations using ASHE dataset, 2021/22.

Table 7: Annual growth in employee nominal gross hourly earnings (per cent) under different weighting schemes, 2004-2005, 2013-2014 and 2021-2022

	2004-2005			2013-2014			2021-2022		
	CSWEIGHT	WATT	Diff.	CSWEIGHT	WATT	Diff.	CSWEIGHT	WATT	Diff.
Mean	12.38	12.69	0.31	5.42	5.63	0.21	9.57	10.14	0.57
p10	-4.88	-4.85	0.02	-6.99	-7.00	-0.01	-5.51	-5.38	0.13
p25	2.09	2.09	0.00	0.00	0.00	0.00	0.63	0.86	0.24
p50	5.93	6.01	0.08	2.05	2.10	0.05	5.00	5.28	0.28
p75	13.66	14.00	0.34	6.99	7.26	0.27	13.56	14.28	0.72
p90	29.76	30.48	0.72	19.67	20.21	0.55	29.47	30.79	1.32
IQR	11.58	11.91	0.33	6.99	7.26	0.27	12.93	13.42	0.48
Direction of growth (col %):									
Negative	14.11	14.04	-0.07	18.39	18.30	-0.08	15.76	15.56	-0.20
Zero	7.09	7.19	0.10	13.71	13.73	0.02	8.56	8.20	-0.37
Positive	78.81	78.77	-0.03	67.90	67.97	0.06	75.68	76.24	0.56
Num. obs.	*106,516*	*106,516*		*121,813*	*121,813*		*76,884*	*76,884*	

Base: all employee jobs paid on adult rates, where no loss of pay due to absence (unless absence due to furlough).
Notes: author calculations using ASHE dataset. Diff. = Difference (WATT – CSWEIGHT), percentage points. 'Zero growth' captures nominal changes with an absolute value of <= 5 pence per hour, to allow for measurement error. The measure of gross hourly earnings includes basic pay, bonus or incentive pay and pay received for other reasons but excludes overtime and shift premium pay (ASHE variable: HRPAYX).

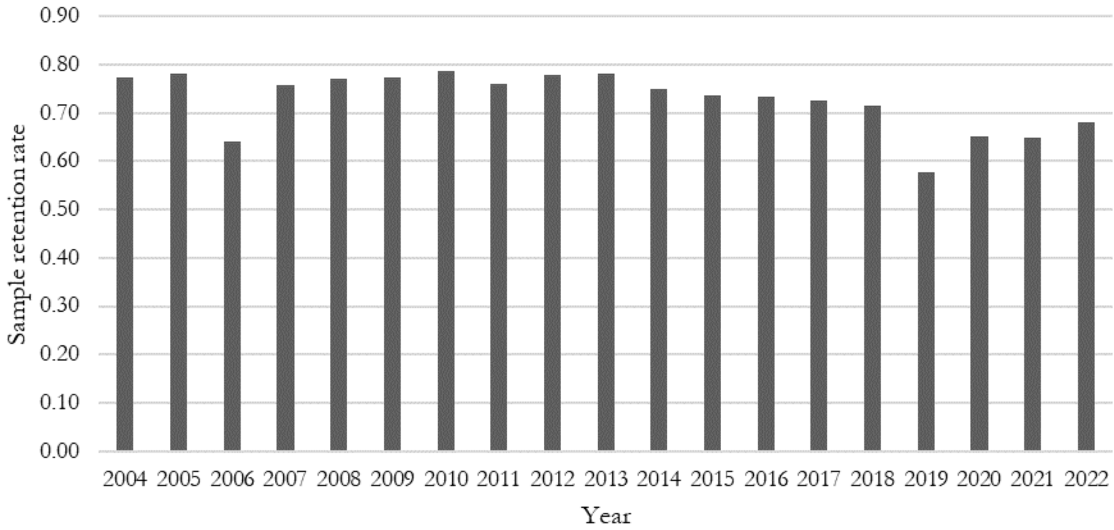
Figure 1: ASHE yield (estimated), by year



Base: all employee jobs in Great Britain.

Notes: Yield estimated by dividing the number of observations in the ASHE research dataset for Great Britain into the estimated total number of employee jobs for Great Britain in the March quarter of each year. Yield is lower in 2007 and 2008 due to cost-saving measures that induced a temporary 20% reduction in the size of the issued sample (ONS, 2007). Underlying values provided in Table A1.

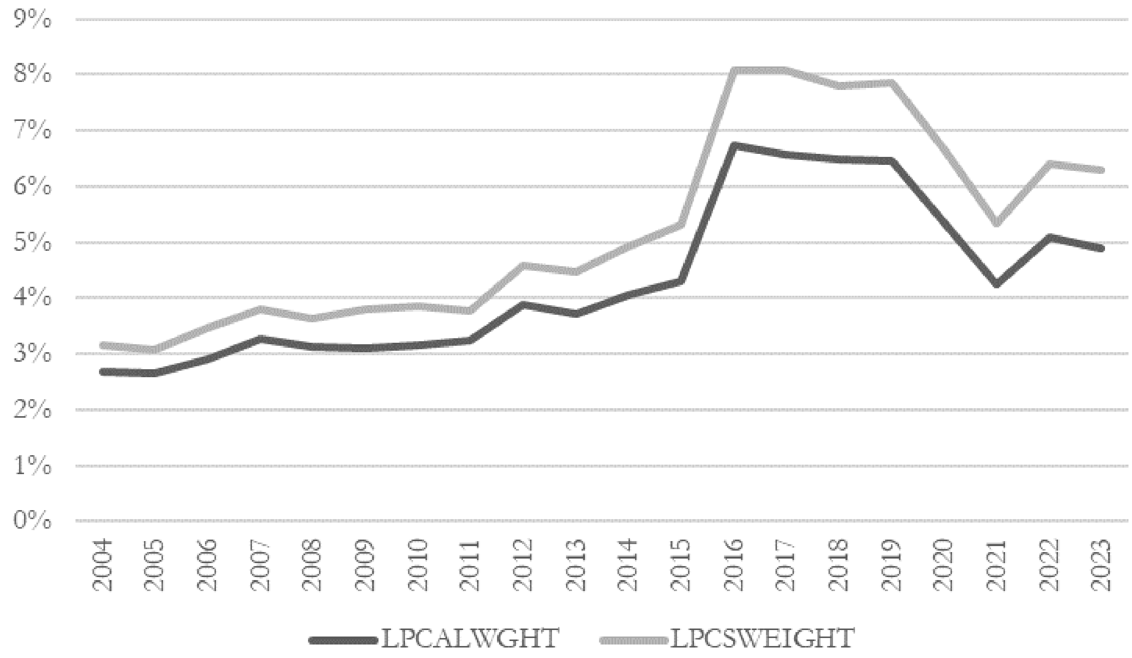
Figure 2: Sample retention rate for individuals from year t to year $t + 1$ (unweighted figures)



Source: ASHE

Base: individual employees appearing in the ASHE achieved sample in year *t*.

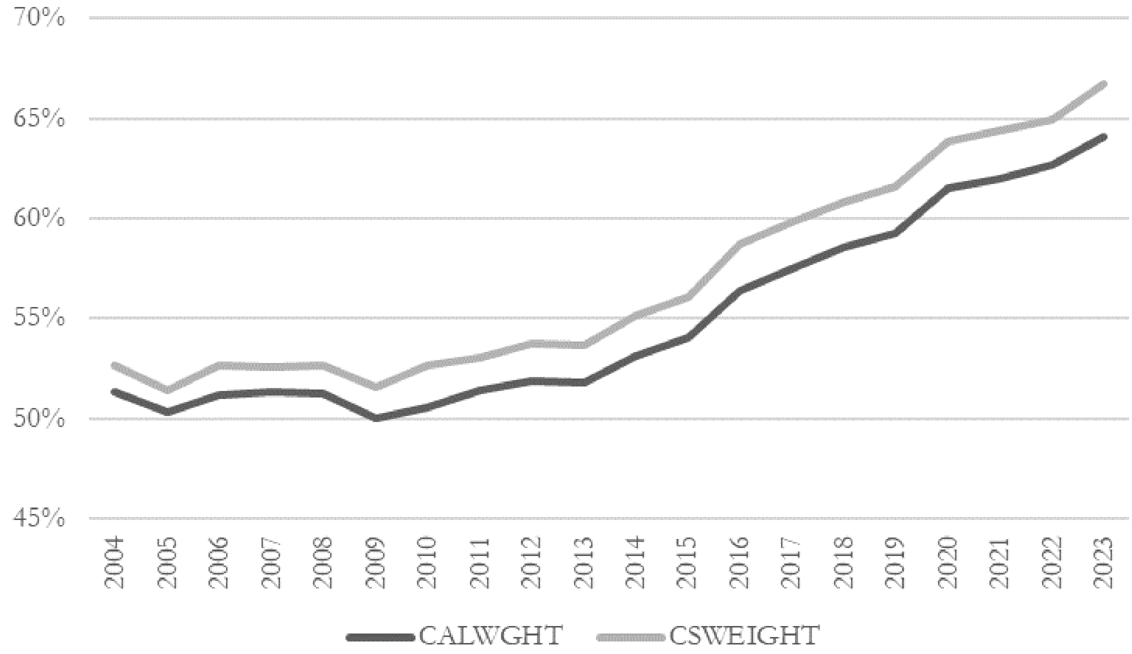
Figure 3: Coverage rate of the adult National Minimum Wage (2004-2015) and National Living Wage (2016-2023) under alternative weighting schemes



Source: ASHE

Notes: All employees aged 25+ (2004,…,2020) or 23+ (2021,..,2023), excluding those with loss of pay due to absence, unless due to furlough (2020 and 2021 only). LPCALWGHT is the original ASHE low pay weight. LPCSWEIGHT is our adjusted weight. Differences between the two series are statistically significant from zero at the 0.1% level in each year. See footnote 15 for our approach to measuring coverage.

Figure 4: Bite of the adult National Minimum Wage (2004-2015) and National Living Wage (2016-2023) – Kaitz Index – under alternative weighting schemes



Source: ASHE

Notes: Bite estimated as the minimum wage expressed as a percentage of the median wage. Median wage estimated for all employees aged 25+ (2004-2020) or 23+ (2021-2023), excluding those with loss of pay due to absence, unless due to furlough (2020 and 2021 only). CALWGHT: median estimated using ASHE standard weight. CSWEIGHT: median estimated using our adjusted standard weight.

Figure 5: Percentage of employees aged 25 (2004,...,2020) or 23+ (2021) paid at the National Minimum Wage (2004,...,2015) or National Living Wage (2016,...,2021) who 'escape' by the following year, under alternative weighting schemes

Source: ASHE

Notes: All employees aged 25+ (2004,…,2020) or 23+ (2021), and paid at the NMW/NLW, excluding those with loss of pay due to absence, unless due to furlough (2020 and 2021 only). LPCSWEIGHT is our adjusted cross-sectional weight; LPCSWATT is our new longitudinal weight. Differences between the two series are not statistically significant in each year.

Figure 6: Percentage of employees aged 25 (2004,...,2020) or 23+ (2021) paid at the National Minimum Wage (2004,...,2015) or National Living Wage (2016,...,2021) who 'escape' by £1 or more by the following year, under alternative weighting schemes

Source: ASHE

Notes: All employees aged 25+ (2004,…,2020) or 23+ (2021), and paid at the NMW/NLW, excluding those with loss of pay due to absence, unless due to furlough (2020 and 2021 only). LPCSWEIGHT is our adjusted cross-sectional weight; LPCSWATT is our new longitudinal weight. 'Escape by £1' refers to £1 in 2023 wages; values deflated using an index of median wages. Differences between the two series are not statistically significant in each year.

Supplementary Appendix

Table A1: Values used to estimate ASHE yield shown in Figure 1, by year

	Employee jobs: UK ('000s)	Employee jobs: NI ('000s)	Employee jobs: GB (‘000s) - estimated	ASHE responses: GB	ASHE yield: GB - estimated
1997	24,697	588	24,109	153,950	0.64%
1998	25,332	609	24,723	161,378	0.65%
1999	25,641	621	25,020	161,750	0.65%
2000	26,097	637	25,460	158,965	0.62%
2001	26,516	649	25,867	161,358	0.62%
2002	26,825	661	26,164	163,821	0.63%
2003	26,866	669	26,197	166,431	0.64%
2004	27,166	681	26,485	166,794	0.63%
2005	27,580	696	26,884	168,343	0.63%
2006	27,831	706	27,125	169,933	0.63%
2007	28,042	715	27,327	140,936	0.52%
2008	28,293	732	27,561	140,703	0.51%
2009	27,899	714	27,185	171,891	0.63%
2010	27,363	708	26,655	175,131	0.66%
2011	27,411	699	26,712	184,501	0.69%
2012	27,703	690	27,013	177,464	0.66%
2013	27,709	695	27,014	180,082	0.67%
2014	28,346	709	27,637	185,762	0.67%
2015	29,198	722	28,476	183,475	0.64%
2016	29,704	730	28,974	179,022	0.62%
2017	30,112	743	29,369	178,943	0.61%
2018	30,252	761	29,491	180,185	0.61%
2019	30,601	774	29,827	177,930	0.60%
2020	30,911	778	30,133	138,385	0.46%
2021	30,394	769	29,625	134,696	0.45%
2022	31,408	796	30,612	141,675	0.46%
2023	32,275	813	31,462	149,372	0.47%

Sources: Employee jobs (UK) are for the March quarter of each year, sourced from ONS (2024c). Employee jobs (NI) for the same quarter are sourced from NISRA (2024). Employee jobs (GB) estimated by subtracting ‘employee jobs (NI)’ from ‘employee jobs (UK)’. Number of ASHE responses (GB) sourced from ONS (2024a).

Table A2: Profile of ASHE sample by employee characteristics, original and alternative ASHE weights, 2023

	ASHE weighted (CALWGHT), per cent	ASHE adjusted weight (CSWEIGHT), per cent	Bias under CALWGHT (2)-(1)	Bias squared
	(1)	(2)	(3)	(4)
Gender:				
Female	49.7	49.1	-0.6	0.4
Male	50.3	50.9	0.6	0.4
Average bias (mean):				*0.4*
Hours:				
Part-time	27.5	29.7	2.2	5.1
Full-time	72.5	70.3	-2.2	5.1
Average bias (mean):				*5.1*
Age group:				
16-19	3.5	4.0	0.5	0.2
20-24	8.0	8.4	0.5	0.2
25-29	11.9	12.0	0.1	0.0
30-34	12.6	12.6	0.0	0.0
35-39	12.0	12.0	-0.1	0.0
40-44	11.2	11.1	-0.1	0.0
45-49	10.6	10.3	-0.2	0.1
50-54	10.8	10.5	-0.3	0.1
55-59	9.7	9.4	-0.3	0.1
60-64	6.6	6.5	-0.1	0.0
65 plus	3.1	3.2	0.1	0.0
Average bias (mean):				*0.1*
Occupation:				
Managers, directors and senior officials	10.4	11.2	0.8	0.6
Professional	28.0	24.8	-3.2	10.4
Associate professional and technical	15.1	14.4	-0.8	0.6
Administrative and secretarial	10.7	11.4	0.7	0.6
Skilled trades	6.3	7.1	0.8	0.6
Caring, leisure and other service	8.2	8.3	0.1	0.0
Sales and customer service	6.3	6.7	0.4	0.2
Process, plant and machine operatives	4.5	4.7	0.2	0.0
Elementary	10.4	11.4	1.0	1.0
Average bias (mean):				*1.6*
N observations	*149,372*	*149,372*		