Non-response Weights for the UK Labour Force Survey? Results from the Census Non-response Link Study

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Summary

This working paper summarises results from work carried out on the Census Non-response Link Study (CNRLS) and discusses their implications for potential adjustment of the Labour Force Survey (LFS) weighting procedures. The CNRLS links survey with census data, where survey fieldwork was carried out close to the 2011 Census day, to provide data for both survey responders and non-responders from the Census. A number of non-response models were derived from the linked data, leading to the definition of several sets of non-response weighting classes. Weighting factors were computed for each set of classes and then applied to Wave 1 LFS survey data for England and Wales from periods around the 2011 Census date. Estimates of economic activity calculated using the standard LFS weighting procedures were then compared to counterpart estimates based on the same weighting procedure but with the additional inclusion of a direct non-response adjustment.

It is shown that in general the non-response factors based on CNRLS data made little difference to the estimates obtained using the current weighting procedure. Differences in the estimates were sought at the overall level and for select subgroups defined by age and sex. However, further domain analysis showed differential non-response existed between ethnic groups, and hence non-response factors based on ethnicity were investigated. It was found that the estimates of levels in all categories of economic activity were affected by non-negligible amounts in some minority ethnic groups; however, the impact on the estimates of rates was modest, indicating that the current weighting procedure did not control for the number of people in each ethnic group. This problem could be addressed if reliable data about ethnicity from an administrative source were to become available and included in the calibration model.

It is unclear if the limited evidence for non-response bias arises because bias is negligible, and so cannot be detected, or because it can only be detected through relationships to variables which are not included in the CNRLS. To investigate these questions further, another set of non-response weights was derived. These weights were calculated from the results of a quality check model, which included employment as a covariate. The results indicated that there may be a small bias in LFS estimates of employment, and that it is more important in women: the suggestion is of a slight underestimation of employment in women and correspondingly a slight overestimation of inactivity.

A census-based non-response weight to be effective would, at a minimum, need to have a non-negligible impact on outcomes and the process it is adjusting for would need to be stable over time. Further evidence suggests that non-response processes have changed since 2011 (though we do not know what the implications of this are for bias): response has continued to decline since the 2001 Census and the LFS fieldwork procedures have also changed – in 2011, around 30 per cent of wave 1 interviews were conducted by telephone but now this has been reduced to around 10-15 per cent. Consequently, even if there is some bias in the LFS, it is unlikely that the census based non-response models will provide a durable solution. Also, the application of non-response weights would introduce extra variability to LFS estimates, which may not be balanced out by any reduction of the potential bias.

Conclusions of the Analysis

1. A non-response weight based on the CNRLS should not be introduced to the LFS at this time.
2. We should explore the use of administrative data sources in the weighting procedure to adjust for differential non-response in relation to population characteristics, such as ethnicity, that are not currently included in the calibration variables.
3. The findings of this study should be used to improve the data collection strategy, by helping to target groups with particularly high levels of non-response.

1. Introduction

LFS response rates have been rapidly declining in recent years: down by around 30 percentage points over the last two decades. When response rates drop, there is an increased risk of non-response bias occurring, where the potential differences between the characteristics of responders and non-responders lead to estimates being distorted, so that they no longer accurately reflect the population. It is important that we understand non-response and do everything we can to reduce its potential effects on estimates, such as the labour market outcomes (LMOs).

This paper considers under what conditions non-response weighting can be efficacious and explores the evidence for bias more generally in the LFS using data from England and Wales[1].

An initial ONS investigation (ONS, Dec 2012) suggested that in particular the number of women in employment was underestimated in the LFS, when compared with the Census figure. It is inappropriate to consider that the census labour market measure is directly equivalent to the LFS measure, given differences in data collection context and content, but we expect the two employment measures, in particular, to be highly correlated, and hence the employment measures from the two sources should be quite similar. We think that the difference between the two measures of employment that was reported in the initial ONS investigation, approximately 600,000 overall, is due in large part to the calibration totals used in the weighting of 2011 LFS data, which were obtained from mid-year estimates based on Census 2001 data, and other data collection and measurement issues (see ONS (2013) for the impact re-weighting using Census 2011 totals has on LFS estimates).

The methods used in the CNRLS to explore possible bias do not rely directly upon the comparison of the LMOs from the two sources. Instead, an attempt is made to:

i. identify factors that are associated with non-response to the LFS using census variables;
ii. create a survey weight based on the non-response rate for different groups;
iii. introduce the non-response weight to the standard survey weighting process and to estimate LMOs;
iv. compare the LMOs produced using the adjusted weight to those produced using the standard weighting procedure but unadjusted for non-response.

In order for a non-response weighting procedure to be effective, it is vital that it be based on population characteristics that are associated with both non-response and LMOs; otherwise their inclusion can be counterproductive and may increase the variance of estimates without making an appropriate adjustment for the bias. The LMO measure considered here is economic activity as defined by employment, unemployment and economically inactive classification.

In Section 2 we describe briefly the dataset from the CNRLS that we used to carry out this work, and in Section 3 we present some descriptive statistics of the observed non-response patterns and a simple analysis of non-response bias where we compare results from 2001 and 2011. In Section 4, we

[1] Linked census-survey data from Scotland were unavailable at the time of the analysis.

describe briefly how the non-response weighting procedure works, and in Section 5 we describe some of the models we considered to define non-response classes. In Section 6, we present results for the impact of the application of the non-response weights on LFS estimates, and in Section 7 we present the case for our decision and some recommendations.

2. The Census Non-response Link Study

The census provides a rare opportunity to compare the socio-demographic characteristics and LMOs of both survey respondents and non-respondents at one point in time (in the decade between censuses), by linking census records to the records of those who were sampled for the LFS.

The 2011 CNRLS (for the LFS) is based on matching 2011 Census records to the sample of LFS Wave 1 cases that were allocated to the field or telephone unit in England and Wales between March and July 2011 (around the time of the Census). The main purpose of this is to compare the characteristics of respondents and non-respondents, which allows us to estimate non-response bias and evaluate methods of non-response adjustment. Similar work was carried out following the last four population censuses (1971, 1981, 1991 and 2001), but each of these found that the addition of a non-response adjustment to the existing weighting methods only had a negligible effect on estimates and therefore they were not implemented; for work based on Census 2001 see Freeth and Sparks (2003). As part of the CNRLS, other surveys have also been linked to census data; in previous studies this led to the implementation of non-response weights on the Living Costs and Food Survey and the General Household Survey.

Data matching and agreement rates

Out of a possible 13,578 eligible records in Wave 1 of LFS data spanning 13 weeks in Q1 and Q2 2011, 12,790 (or 94.2%) were successfully matched to census-occupied households – see Table 1. It is assumed that the census household at the matched address is the same household as that surveyed. Households classed as ineligible for the LFS and those with unknown eligibility have been excluded from these analyses. We can see from Table 1 that the response rate in the matched dataset is slightly higher than that of the set of eligible households.

Table 1. Match rates between the LFS and Census 2011

	All LFS eligible households	Matched to Census occupied
Number of records	13,578	12,790
Co-operation rate	61.0%	62.2%
Non-contact rate	12.6%	11.6%
Refusal and other non-response rate	26.4%	26.2%

The census data includes variables at both the household and individual level, many of which have been available for use within the analyses. However, in practice, mostly household level variables are usable because matches at the person level are more difficult to establish and less reliable. Consequently, the only person level socio-demographic characteristics that have been available have been those associated with the Household Reference Person (HRP). These include variables such as age, sex, marital status, highest qualification, National Statistics Socio-Economic Classification (NS-SEC), disability, religion, ethnicity and country of birth. Household level variables include region, household structure, tenure, accommodation type, whether the household is in an urban or rural area and the number of usual residents in the household. Those variables with a sufficiently high agreement rate (set at a minimum of 80%) were examined in more detail – see Table 2 for a list of the variables considered in the regression models.

Table 2. **Variables considered for inclusion in the regression analysis**

Variable	Match Rate (%)
Urban/Rural indicator	N/A
Region	N/A
HRP Sex	99.8
HRP UK born	99.6
HRP Ethnicity	97.6
HRP Marital status	96.0
No of dependent children	95.6
No of usual residents	92.7
HRP Age group	90.4
HRP Disability	89.9
Tenure	89.2
Household structure	89.2
HRP Religion	82.7
Accommodation type	81.6
HRP Health	60.5
HRP highest qualification	57.0
HRP NS-SEC (socio-economic category)	44.5

3. Non-response Patterns in the LFS

The linked dataset allowed us to compute response rates by a number of factors available in the Census. For example, Table 3 shows the response rates by the economic status in the Census of the HRP (the HRP census employment status has about 96% agreement rate with the equivalent LFS variable).We can see that the employed have a slightly lower response rate than the unemployed, 61.3% against 62.1%. Households where the HRP is retired or looking after home/family show the highest response rates, 65.6% and 63.8% respectively.

Table 4 shows the response rates by ethnic group; we can see that the response rates range from 53.2% for the Chinese group to 66.4% for the Indians group. People in the White British group, who represent nearly 90% of the population, show a 62.6% response rate.

Table 3. Response rates by the Census economic status in the LFS Q1-Q2 2011

	Number of households	Response rate
Unknown	656	59.8%
Employee	6,787	61.3%
Self-employed	1,379	61.7%
Unemployed	335	62.1%
Student	105	59.0%
Retired	2,618	65.6%
Long-term sick/disabled	458	60.0%
Looking after home/family	240	63.8%
Other	206	61.7%
Under 16	6	33.3%
All	12,790	62.2%

Table 4. Response rates by ethnic group in the LFS Q1-Q2 2011

	Number of households	Response rate
White British	10,737	62.6%
Other White and mixed White	685	61.2%
Indian	247	66.4%
Pakistani	128	64.1%
Bangladeshi	58	65.5%
Chinese	62	53.2%
Black African	175	64.0%
Black Caribbean	156	54.5%
Other	213	59.2%
Unknown	329	53.2%
All	12,790	62.2%

Comparing response patterns of 2001 and 2011

A comparison of the response rates in 2001 and 2011 (see Table 5) shows that in 2001 the response rate for the unemployed is more than five percentage points lower than the response rate of those who are employees. However, in 2011, for the households where the HRP is unemployed the response rate is slightly higher than that in households where the HRP is an employee. This indicates that non-response mechanisms have changed since 2001, and it is possible that they will change in the future.

Table 5. Comparing responses rates between 2001 and 2011 (in percent)

	2001	2011
Employee	81.1	61.3
Self-employed	78.1	61.7
Unemployed	74.6	62.1
Retired	81.2	65.6
Looking after home or family	80.7	63.8

Non-response bias

Differential non-response can lead to bias in estimates; an expression of the bias, or relative bias, can be obtained for simple non-response mechanism models. For example, under the deterministic non-response model, see Särndal et al (1992), the bias of the expansion estimator of the mean of variable y based on the responders set, $\hat{Y}_{\pi r}$, is given by

$$B(\hat{Y}_{\pi r}) = nr(\bar{y}_{Ur} - \bar{y}_{Unr})$$

where nr is the non-response rate and $\bar{y}_{Ur}$ and $\bar{y}_{Unr}$ are the mean values of y for the subpopulations of responders, Ur, and non-responders, Unr, respectively.

For the HRP population, we can use the information in Table 5 to estimate the bias of the estimate of the rates of employment and unemployment, as defined by the economic activity variable in the Census. We can see from Table 6 that the difference in employment rates between responders and non-responders to the LFS is much smaller in 2011 compared to 2001 (0.4% against 1.2%), and so the resulting bias for the employment rate in 2011 is similar to that in 2001 even though the non-response rate has doubled between 2001 and 2011. For the unemployment rate, the magnitude of the bias is smaller in 2001 than in 2011: the unemployment rate in the HRP population is overestimated by about 0.1% in 2011, whereas in 2001 it is underestimated by 0.3%.

Table 6. Bias estimates in the HRP population

	2001			2011		
	Responders	Non-responders	Bias estimate	Responders	Non-responders	Bias estimate
Employment rate	84.4%	83.2%	0.2%	80.4%	80.0%	0.2%
Unemployment rate	3.4%	4.8%	-0.3%	4.0%	3.9%	0.1%

The above analysis is limited to the HRP population and is based on economic activity as defined in the Census and hence it is only indicative of the bias in the LFS estimates. We next investigate non-response bias in the whole population through the application of a non-response weight, and base the analysis on LFS data.

4. Non-response Weighting

The LFS weight in the current procedure is a product of the design weight, which incorporates the selection probability of the survey elements, and a calibration weight, which adjusts the design weights in such a way that the sums of the weights match population totals for the variables included in the calibration model. Calibration adjusts for imbalances in the selected sample and the responders set with respect to the characteristics captured in the calibration model (location, sex and age). Consequently, when survey outcomes are related to the calibration variables, this calibration adjustment improves the precision of estimated outcomes. When the characteristics of non-responders are related both to the calibration variables and the outcomes, then calibration also adjusts for non-response bias.

The proposed non-response weighting procedure includes partitioning the data into a number of non-response classes, defined by particular sub-group characteristics, and creating a weight for each class. The weight is created as the inverse of the response rate for the group defined by the class.

Once the non-response factors have been created, they can be incorporated into the LFS weighting procedure. As we have concentrated on the characteristics of the HRP, this has involved matching each HRP to their corresponding non-response factor, applying this factor to everyone within the same household (so that they all receive the non-response factor of the HRP), multiplying the non-response factors by each person's existing LFS weight and then calibrating the sample to known population totals by age, sex and region. Estimates created with and without the non-response weights can then be compared in order to analyse their effect. A small effect would signify that the non-response weights are not correcting for any potential non-response bias, whereas a large effect would tell us the opposite: that the weights are having an effect and that they are correcting for non-response bias.

Requirements for effective non-response weights

In order for non-response weights to have a significant impact on the resulting estimates, there are three key requirements: the response propensities of the different classes need to vary as widely as possible, the outcomes being measured (which in this case are LMOs) need to be strongly associated with the non-response classes, see Zhang et al (2013), and the non-response mechanism needs to be stable. Stability is important because if the mechanism was to be applied continually until the next opportunity to review its effectiveness, then this is likely to mean waiting until after the next census, when another CNRLS project could be carried out. If the response propensities of the different classes are likely to change significantly over the next ten years, then the non-response weights would become less effective and could be effectively creating bias in the estimates instead of reducing it.

5. Defining Non-response Classes

A number of logistic models of differing levels of complexity have been examined, where response and non-response (because of non-contact or refusal) have been classified into a binary outcome. The models vary from a simplistic univariate breakdown (based, for example, on ethnicity) through to much more complex models that would be challenging[2] to employ in a production environment but give the opportunity to explore inter-relationships between variables. Several different methods have been utilised to create the models and some examples of these models and the process of creating them are described over the next few pages.

There is no easy answer to the question of how many non-response weighting classes are required. Too few categories may not capture well the differences between subgroups in the population; too many classes and the model may not be robust, particularly if some weighting classes have small sample sizes.

Some non-response models

Below are five of the models that have been created, with details of how they were created and what effect they have on labour market outcome estimates.

1) Univariate model (Ethnicity-based model)

From Table 7 it is clear that there is differential non-response between ethnic groups, with the Black Caribbean and Chinese groups showing the lowest response rates, around 54%, whereas the Asian groups other than the Chinese group show the highest rates, between 64% and 66%. The largest group, which comprises nearly 90% of the population, has a response rate of just over 62%.

The simplest model was based on a six-category ethnicity variable (White, Mixed, Asian, Black, Other and Missing), leading to six non-response weighting classes. The non-response factor was

[2] The challenge arises largely from having many classes and hence a potentially unstable solution.

calculated by dividing the census count by the LFS response count in the analysis dataset within each group; the resulting factors were then scaled (Table 7).

Table 7. Scaled non-response weighting factor values based on ethnic group

Ethnicity	Scaled factor
White	0.93
Mixed	1.02
Asian	0.91
Black	1.00
Other	1.04
Unknown/Missing	1.10

2) Multivariate model

It is thought that having an adjustment based on a single variable may not be sufficient as non-response will likely vary by more than one variable. Therefore, we sought to identify which variables, among the candidates variables mentioned above, were most associated with non-response. For this, logistic regression was performed with response/non-response as the dependent variable, and the set of candidate variables as model covariates. It was age, region, whether the HRP was born in the UK and household structure that were found to be the most significant, with ethnicity dropping out of the model, although this is correlated to whether the HRP was born in the UK. Age and region acted as control variables[3], as both of these variables are included within the calibration. The model was then simplified by collapsing categories within variables and testing the effect on the AIC (a measure of the explanatory power of the model whilst considering the degrees of freedom). This method was used to explore a number of other models, all of which showed similar results.

Some age groups and regions were combined, which resulted in 4 groups for each of these two variables. The categories of household structure were combined, which resulted in two groups (Single Adult households; and Other); the variable "whether the HRP was born in the UK" was binary. Hence, the resulting model had 64 non-response classes (4*4*2*2 = 64).

Non-response weighting factors were then computed for each of the 64 classes. See Appendix A for the model breakdown with factors values.

3) Tree model

Regression tree modelling (e.g. CHAID) is commonly used to create non-response classes. However, the software was unavailable in the secure census data management environment, and hence we simulated tree-based models using outputs from logistic regression.

This method involved looking at the variables that are most highly correlated with non-response in the logistic model, and seeing which categories within those variables behave the most differently to each other in terms of response (these contrasting categories were identified using Chi-squared tests). For example, the region of Yorkshire and the Humber had a noticeably higher response rate than all of the other regions, so a model was created by taking everyone from this region and separating them off into a category of their own (so that they become the first level of the model's dependent variable). Next, analysis of all of the remaining cases (which for this model refers to those who live elsewhere) was carried out to determine the next most important split of the data. This process continued until no further splits gave groups with noticeably different response propensities. One of the models created in this way had classes defined by region, age group of the HRP, household structure, tenure, country

[3] Age, sex and region are already accounted for in the LFS weighting through their use as population calibration controls. We attempted to identify non-response factors that were influential over and above any association with these calibration control variables.

of birth of the HRP and an urban/rural indicator. Again, non-response weighting factors for each of the classes identified by the tree splitting were computed from the analysis dataset (Table 8).

Table 8. Tree model with non-response factors

<table>
<tr><th>Region</th><th>HRP age group</th><th>Household structure</th><th>Tenure</th><th>Country of birth</th><th>Urban / rural indicator</th><th>HRP age group</th><th>Scaled Factor</th></tr>
<tr><td>Yorkshire and Humberside</td><td colspan="6"></td><td>0.92</td></tr>
<tr><td rowspan="7">Other regions</td><td colspan="6">HRP aged 65-74</td><td>0.95</td></tr>
<tr><td rowspan="6">HRP other age</td><td colspan="5">1 adult only</td><td>1.15</td></tr>
<tr><td rowspan="5">Other household structure</td><td colspan="4">Owned outright</td><td>0.99</td></tr>
<tr><td rowspan="4">Other tenure</td><td colspan="3">HRP born outside the UK</td><td>0.95</td></tr>
<tr><td rowspan="3">HRP born in the UK</td><td colspan="2">Rural</td><td>1.01</td></tr>
<tr><td rowspan="2">Urban</td><td>HRP aged 35-54</td><td>1.04</td></tr>
<tr><td>HRP other age</td><td>1.00</td></tr>
</table>

4) Quality-Check Model

The census measure of economic activity is used in a special model to assess the quality of potential bias adjustment made by other variables in the model. The model contains, among other variables, a binary indicator of ‘whether the HRP is employed’, and has been tested to see what effect this has on estimates. The aim of this model is to assess the extent to which variables included in the adjustment model proxy the differential non-response related to the census economic activity status. As well as the HRP employment indicator, the model contains aggregated versions of the variables: region, age group of the HRP, tenure and household structure. This model is unlikely to be stable over time, and hence it should not be used in practice, but it is useful for validation purposes at the time of the Census. See Appendix B for model classes with their non-response weighting factors.

Goodness of fit of the models

The “best” logistic models explored in the study were still a poor fit to the data. The quality of standard regression models can be evaluated partly by the amount of variation “explained” in the outcome variable. An equivalent “pseudo” measure of this statistic is available for logistic models and, for all non-response models it was extremely low, indicating a poor fit to the data. Despite this, a number of socio-demographic factors were statistically significant in the various models but the association was not especially strong. In conclusion, the set of available census variables had only a fairly limited capacity to predict non-response, although we were able to utilise a few that appeared to have some promise of success.

6. Applying Non-response Factors - Overall Effectiveness of the Models

Sets of weights were produced from a range of models to explore their effects on LMOs using LFS Wave 1 data from the quarter covering Jan-Mar 2011. The non-response adjustment factors computed from a subset of models were also applied to Wave 1 data collected in other quarters of the year to ensure the results were not unusually sensitive to a particular time point.

Impact on estimates by ethnicity of the ethnicity-based factors

For estimates of levels, some minority ethnic groups showed notably lower employment levels, whereas in other groups employment increased notably. The effect on labour market rates was, however, less important by the ethnic group domain. For example, Table 9a shows that the number of employed people in the Asian group would be about 3% lower when the factors are applied; for the Black ethnic group the adjusted estimate would be 6% higher. However, as can be seen from Table 9b, the adjusted employment rates would be only 0.1% lower for the Asian group and 0.2% higher for the Black group.

Table 9a. Impact of ethnicity factor on employment level estimates of ethnic groups

Ethnicity	No factor and calibration Level (in 000s)	Factor and calibration Level (in 000s)	Percentage difference
White	22,020	21,989	-0.1
Mixed	191	199	4.1
Asian	1,504	1,458	-3.1
Black	600	635	6.0
Other	402	428	6.6
Unknown/Missing	9	10	15.6

Table 9b. Impact of ethnicity factor on employment rate estimates of ethnic groups (in percent)

Ethnicity	No factor and calibration Employment rate	Factor and calibration Employment rate	Difference
White	71.2	71.2	0.0
Mixed	56.2	56.5	0.3
Asian	60.7	60.7	-0.1
Black	53.0	53.2	0.2
Other	63.1	62.9	-0.3
Unknown/Missing	54.3	54.4	0.1

Impact of non-response factors on estimates by age and sex

When considering the impact of the ethnicity based non-response adjustments on the population as a whole, or by sex and age domain groups, non-response weighting showed only a slight impact on labour market levels or rates. In effect, the impact on levels for the relatively small numbers in the minority ethnic groups in the sample was swamped by the much larger number in the White ethnic group, where the non-response adjustment had no impact. The ethnicity-based model, multivariate model and tree model all show similar results, as can be seen from Table 10a. The estimates of rates are also similar with and without adjustment (Table 10b).

Because the quality check model includes employment in the definition of its non-response classes, it allows us to obtain an estimate of the possible bias of the current procedure. Based on this model, Table 10a shows that the current procedure appears to underestimate employment by about 110,000, but the bias of unemployment appears negligible. The estimated bias in the level of employment is more important in women than men, about 80,000 against 30,000.

Table 10a. Impact of non-response factors on labour market levels (in 000s)

	Employment status	No model	Ethnicity factor	Multivariate model	Tree model	Quality check model
All	Employed aged 16-64	24,726	24,719	24,725	24,725	24,833
	Employed 65+	793	792	796	796	820
	Unemployed aged 16-64	2,032	2,039	2,045	2,046	2,031
	Unemployed aged 65+	19	19	19	19	20
	Inactive aged 16-64	8,789	8,789	8,777	8,776	8,683
	Inactive aged 65+	8,037	8,037	8,034	8,034	8,009
Male	Employed aged 16-64	13,242	13,234	13,214	13,213	13,272
	Employed 65+	463	463	463	465	478
	Unemployed aged 16-64	1,221	1,226	1,234	1,234	1,221
	Unemployed aged 65+	14	14	14	14	15
	Inactive aged 16-64	3,267	3,271	3,283	3,284	3,237
	Inactive aged 65+	3,516	3,516	3,516	3,514	3,502
Female	Employed aged 16-64	11,483	11,485	11,511	11,512	11,561
	Employed 65+	330	329	332	331	342
	Unemployed aged 16-64	811	813	812	812	810
	Unemployed aged 65+	5	5	5	5	5
	Inactive aged 16-64	5,522	5,518	5,494	5,492	5,445
	Inactive aged 65+	4,520	4,521	4,518	4,519	4,508

Table 10b shows that employment rate appears to be potentially underestimated by around 0.3%, whereas the rate of inactivity is overestimated by nearly the same amount – the unemployment rate seems to show very little apparent bias. When looking at breakdowns by sex, it can be seen that potential bias in the employment rate is stronger in females (0.44% compared to 0.16% in males).

Table 10b. Impact of non-response factors on labour market rates (in percent)

		No model	Ethnicity factor	Multivariate model	Tree model	Quality check model
All	Employment rate	69.6	69.5	69.6	69.6	69.9
	Unemployment rate	7.4	7.5	7.5	7.5	7.4
	Inactivity rate	24.7	24.7	24.7	24.7	24.4
Males	Employment rate	74.7	74.6	74.5	74.5	74.9
	Unemployment rate	8.3	8.3	8.4	8.4	8.2
	Inactivity rate	18.4	18.4	18.5	18.5	18.3
Females	Employment rate	64.5	64.5	64.6	64.6	64.9
	Unemployment rate	6.5	6.5	6.5	6.5	6.4
	Inactivity rate	31.0	31.0	30.8	30.8	30.6

Taken as a whole, the results show that both levels and rates of employment, unemployment and inactivity tend to be affected only negligibly by the inclusion of non-response adjustments. An exception was the ethnicity-based model, which caused some changes in levels but not rates. Consequently, the results generally argue against the inclusion of a non-response weight, although the findings for outcome levels potentially provide tentative support to the counter proposal for a weight based on the ethnicity domain for economic activity levels.

7. Conclusion

A census-based non-response weight to be effective would, at a minimum, need:

i. to have a non-negligible impact on outcomes and,
ii. be based on a response process that is stable over time.

The results of this project have shown that non-response adjustments have a negligible impact on estimates for the key publication groups explored here, except for Ethnicity. However, while the impact on levels within minority ethnic groups is notable, the impact on rates is negligible. Furthermore, given that ethnic groups other than "White" are rather small, the calculated factors from the CNRLS data may not be very reliable.

Further evidence suggests that non-response processes have changed since 2011 (though we do not know what the implications of this are for bias): response has continued to decline since the Census and the LFS fieldwork procedures have also changed – in 2011, around 30 per cent of wave 1 interviews were conducted by telephone but now this has been reduced to around 10-15 per cent. A forthcoming CNRLS report will show that non-response to telephone surveys differs from that for face-to-face surveys, with young people in particular being affected.

As response patterns can change over time, non-response adjustments based on Census 2011 may not be appropriate in the future. Consequently, even if there was some bias in the LFS, it is unlikely that the census based non-response models would provide a durable solution. Also, the application of non-response weights would introduce extra variability to LFS estimates, which may not be balanced out by any reduction of the potential bias. We hence make the following conclusions:

1. A non-response weight based on the CNRLS should not be introduced to the LFS at this time.
2. We should explore the use of administrative data sources in the weighting procedure to adjust for differential non-response in relation to population characteristics, such as ethnicity, that are not currently included in the calibration variables.
3. The findings of this study should be used to improve the data collection strategy, by helping to target groups with particularly high non-response.

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Appendices

Appendix A – Multivariate model - non-response factor values

Region	Age group	Household structure	Country of birth of HRP	Scaled Factor
London, South East, East of England	HRP age missing, 18-34,75+	1 adult only	UK	1.15
			Other	1.11
		Other household structures	UK	1.00
			Other	0.98
	HRP age 35-54	1 adult only	UK	1.26
			Other	1.21
		Other household structures	UK	1.08
			Other	1.05
	HRP age 55-64	1 adult only	UK	1.14
			Other	1.10
		Other household structures	UK	1.00
			Other	0.97
	HRP age 65-74	1 adult only	UK	1.07
			Other	1.04
		Other household structures	UK	0.95
			Other	0.92
Wales, South West	HRP age missing, 18-34,75+	1 adult only	UK	1.11
			Other	1.07
		Other household structures	UK	0.97
			Other	0.95
	HRP age 35-54	1 adult only	UK	1.21
			Other	1.16
		Other household structures	UK	1.04
			Other	1.01
	HRP age 55-64	1 adult only	UK	1.10
			Other	1.06
		Other household structures	UK	0.97
			Other	0.94
	HRP age 65-74	1 adult only	UK	1.03
			Other	1.00
		Other household structures	UK	0.92
			Other	0.90
North East, North West,	HRP age missing,	1 adult only	UK	1.06
			Other	1.03

East Midlands, West Midlands	18-34,75+	Other household structures	UK	0.94
			Other	0.92
	HRP age 35-54	1 adult only	UK	1.15
			Other	1.12
		Other household structures	UK	1.01
			Other	0.98
	HRP age 55-64	1 adult only	UK	1.06
			Other	1.03
		Other household structures	UK	0.94
			Other	0.91
	HRP age 65-74	1 adult only	UK	1.00
			Other	0.97
		Other household structures	UK	0.89
			Other	0.87
Yorkshire and Humberside	HRP age missing, 18-34,75+	1 adult only	UK	0.97
			Other	0.95
		Other household structures	UK	0.87
			Other	0.86
	HRP age 35-54	1 adult only	UK	1.04
			Other	1.01
		Other household structures	UK	0.93
			Other	0.90
	HRP age 55-64	1 adult only	UK	0.97
			Other	0.94
		Other household structures	UK	0.87
			Other	0.85
	HRP age 65-74	1 adult only	UK	0.92
			Other	0.90
		Other household structures	UK	0.84
			Other	0.82

Appendix B – Quality check model - factor values

Region	Age group of the HRP	Household structure	HRP employment indicator	Tenure	Scaled Factor
London, South East, East of England	HRP age missing, 18-34, 55-64, 75+	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.10
				Other tenure	1.13
			HRP employed	Owned outright	1.17
				Other tenure	1.20
		2 adults	HRP not employed	Owned outright	0.96
				Other tenure	0.97
			HRP employed	Owned outright	1.00
				Other tenure	1.02
		2+ adults	HRP not employed	Owned outright	1.00
				Other tenure	1.02
			HRP employed	Owned outright	1.05
				Other tenure	1.08
	HRP age 35-54	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.17
				Other tenure	1.20
			HRP employed	Owned outright	1.24
				Other tenure	1.27
		2 adults	HRP not employed	Owned outright	1.00
				Other tenure	1.02
			HRP employed	Owned outright	1.05
				Other tenure	1.07
		2+ adults	HRP not employed	Owned outright	1.05
				Other tenure	1.08
			HRP employed	Owned outright	1.11
				Other tenure	1.14
	HRP age 65-74	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.08
				Other tenure	1.11
			HRP employed	Owned outright	1.14
				Other tenure	1.17
		2 adults	HRP not employed	Owned outright	0.94
				Other tenure	0.96
			HRP employed	Owned outright	0.98
				Other tenure	1.00
		2+ adults	HRP not employed	Owned outright	0.99
				Other tenure	1.01
			HRP employed	Owned outright	1.03
				Other tenure	1.06
Wales, South	HRP age	Missing, 1 adult	HRP not	Owned outright	1.07

West	missing, 18-34, 55-64, 75+	(with or without dependent children)	employed	Other tenure	1.10
			HRP employed	Owned outright	1.13
				Other tenure	1.16
		2 adults	HRP not employed	Owned outright	0.93
				Other tenure	0.95
			HRP employed	Owned outright	0.98
				Other tenure	1.00
		2+ adults	HRP not employed	Owned outright	0.98
				Other tenure	1.00
			HRP employed	Owned outright	1.03
				Other tenure	1.05
	HRP age 35-54	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.13
				Other tenure	1.16
			HRP employed	Owned outright	1.20
				Other tenure	1.23
		2 adults	HRP not employed	Owned outright	0.97
				Other tenure	0.99
			HRP employed	Owned outright	1.02
				Other tenure	1.04
		2+ adults	HRP not employed	Owned outright	1.02
				Other tenure	1.05
			HRP employed	Owned outright	1.08
				Other tenure	1.10
	HRP age 65-74	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.05
				Other tenure	1.08
			HRP employed	Owned outright	1.11
				Other tenure	1.14
		2 adults	HRP not employed	Owned outright	0.92
				Other tenure	0.94
			HRP employed	Owned outright	0.96
				Other tenure	0.98
		2+ adults	HRP not employed	Owned outright	0.96
				Other tenure	0.98
			HRP employed	Owned outright	1.01
				Other tenure	1.03
North East, North West, East Midlands, West Midlands	HRP age missing, 18-34, 55-64, 75+	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.03
				Other tenure	1.06
			HRP employed	Owned outright	1.09
				Other tenure	1.11
		2 adults	HRP not employed	Owned outright	0.91
				Other tenure	0.92
			HRP employed	Owned outright	0.95
				Other tenure	0.96
		2+ adults	HRP not employed	Owned outright	0.95
				Other tenure	0.97

			HRP employed	Owned outright	0.99
				Other tenure	1.01
	HRP age 35-54	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.09
				Other tenure	1.11
			HRP employed	Owned outright	1.15
				Other tenure	1.18
		2 adults	HRP not employed	Owned outright	0.94
				Other tenure	0.96
			HRP employed	Owned outright	0.99
				Other tenure	1.01
		2+ adults	HRP not employed	Owned outright	0.99
				Other tenure	1.01
			HRP employed	Owned outright	1.04
				Other tenure	1.06
	HRP age 65-74	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	1.01
				Other tenure	1.04
			HRP employed	Owned outright	1.07
				Other tenure	1.09
		2 adults	HRP not employed	Owned outright	0.90
				Other tenure	0.91
			HRP employed	Owned outright	0.93
				Other tenure	0.95
		2+ adults	HRP not employed	Owned outright	0.93
				Other tenure	0.95
			HRP employed	Owned outright	0.97
				Other tenure	0.99
Yorkshire and Humberside	HRP age missing, 18-34, 55-64, 75+	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	0.95
				Other tenure	0.97
			HRP employed	Owned outright	0.99
				Other tenure	1.02
		2 adults	HRP not employed	Owned outright	0.85
				Other tenure	0.86
			HRP employed	Owned outright	0.88
				Other tenure	0.90
		2+ adults	HRP not employed	Owned outright	0.88
				Other tenure	0.90
			HRP employed	Owned outright	0.92
				Other tenure	0.93
	HRP age 35-54	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	0.99
				Other tenure	1.01
			HRP employed	Owned outright	1.04
				Other tenure	1.07
		2 adults	HRP not employed	Owned outright	1.00
				Other tenure	0.89
			HRP	Owned outright	0.91

			employed	Other tenure	0.93
		2+ adults	HRP not employed	Owned outright	0.92
				Other tenure	0.93
			HRP employed	Owned outright	0.96
				Other tenure	0.97
	HRP age 65-74	Missing, 1 adult (with or without dependent children)	HRP not employed	Owned outright	0.94
				Other tenure	0.95
			HRP employed	Owned outright	0.98
				Other tenure	1.00
		2 adults	HRP not employed	Owned outright	0.84
				Other tenure	0.85
			HRP employed	Owned outright	0.87
				Other tenure	0.88
		2+ adults	HRP not employed	Owned outright	0.87
				Other tenure	1.00
			HRP employed	Owned outright	0.90
				Other tenure	0.92