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Equality Monitoring 2017/18: Technical Annexes

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Annex A: Notes on data

A.1 Working-age populations

A.1.1 Reporting locations

To compare the diversity of staff in post with local working-age populations, we attached each building where staff were located to a Reporting Location, e.g. London, Swansea, etc. So all staff based in London, for example, were considered as being in one location, irrespective of which part of London they were located in.

For each Reporting Location we identified a catchment area and generated local working-age population figures based on data for that catchment area.

A catchment area would typically include the relevant Local Authority area for the Reporting Location, plus neighbouring Local Authorities, as agreed with each Agency. For example, the London Reporting Location included the working-age population of all the London boroughs as well as those counties that border them.

A detailed list of catchment areas may be seen in Annex C.

A.1.2 Data sources

The UK population dataset at Local Authority[1] level is from the **Annual Population Survey (APS).** This survey is a combined survey of households in the United Kingdom, updated quarterly and available at Local Authority level and above. It is a residence-based labour market survey which includes population and economic activity, broken down by gender, age, race, industry, and occupation[2].

The majority of DfT agencies have staff based only in Great Britain, but the Maritime and Coastguard Agency (MCA) also has staff working in Northern Ireland. Where a nationwide population comparison was required, the GB working-age population (i.e. not including Northern Ireland) was used. The exception was MCA, which was compared with the UK.

APS data used in the 2017/18 Equality Monitoring reports were based on the one-year period October 2016 - September 2017, and downloaded from www.nomisweb.co.uk ("Nomis") on 6th June 2018.

A.1.3 Population

Population data at Local Authority level from the APS were combined with **mid-year** (30 June) **population estimates** for 2016 – the most recent year available when we started our analysis. These were also available at Local Authority level and were based upon results from the 2011 Census with allowance for under-enumeration. These figures covered the entire population, not just the working-age population, so to estimate the

[1] Local authorities including County Councils rather than District Councils.

[2] Further information on the survey can be found at https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/qmis/annualpopulationsurveyapsqmi

working-age population (those aged 16-64 years) we took the number of males and females aged 15-64 years[3] (only five-year age bands were available).

A.1.4 Disability status

The APS questions relating to disability changed in 2014, and respondents are now questioned about "physical or mental health conditions or illnesses" instead of "health problems or disabilities". We did not include this dataset as a comparison with staff disability for the 2013/14 Equality Monitoring reports as it was a new item that did not appear to be comparable enough. Staff data collection tends to simply ask for an indication of "Declared Disabled" or "Disabled".

From 2014/15, we once again started to use the disability dataset, since it is the most appropriate dataset in the APS, and the questions asked were intended to measure disability.

A.1.5 Race

APS data were available for the following ethnic groups:

- Mixed;
- Indian;
- Pakistani/Bangladeshi;
- Black/Black British; and
- Other.

For our analysis, we have combined all the above into a single Black, Asian, and Minority Ethnic BAME category.

A.2 Other data notes

A.2.1 Sickness absence data

For DfTc and all agencies, data were available on the number of days of recorded sickness absence for each member of staff, with one record per incidence.

A.2.2 Definition of staff in post

Staff analysis has been performed using the ONS data specification: people are considered as being in scope of analysis if they are **paid by the department**, rather than if they are currently working in the department.

This differs from the approach taken in the analysis prior to 2014/15. As a result, some staff that were in scope in reports prior to 2014/15, are not covered in this year's analysis. For example, staff who are loaned out but still paid by DfT are in scope by the

[3] Please note that as of August 2010, the official definition of "working-age" expanded to include both males and females aged 16-64 years old; this reflects a planned change in the female state pension age. All have been included in our working-age populations.

current ONS definition, but would have been considered out of scope in the 2013/14 analysis.

Working pattern

No adjustment has been made to absence records for part-time staff. The analysis has been performed on the number of days absent (i.e. how many days of work were recorded as missed).

If the analysis suggests that part-time staff had significantly more sickness absence, then we can be confident that this finding is correct. i.e. we are saying that they were absent for more actual calendar days than other staff - not making any allowance for the fact that they may have been due to work fewer calendar days in the first place.

However, given that part-time staff have fewer available working days, the reverse result (part-time staff having significantly less absence) may not be a meaningful finding.

Annex B: Analytical approach

Two statistical approaches have been used to test for differences in the data: univariate methods that test one variable at a time and multivariate methods that compare several variables simultaneously. Wherever possible, multivariate methods have been used.

B.1 Multivariate methods – Regression Analysis

The main technique used to analyse data taking into account several factors simultaneously was regression: either multiple, logistic, Poisson or negative binomial.

Regression attempts to predict a dependent variable (e.g. the amount of sickness absence taken) using one or more independent variables (such as gender, age etc). In using multiple regression, the principle is to find the "line of best fit" by minimising the sum of the squared distance from the fitted line to each observation. (This approach is sometimes referred to as ordinary least squares regression). The aim is to find a set of independent variables that have a significant relationship with the dependent variable.

Much of the datasets that were analysed had a binary (0/1) result, for example, was in a grade or not; obtained the top performance rating or did not; was selected for interview or was not etc. This type of data lends itself to being analysed using logistic regression. Logistic regression is analogous to ordinary least squares regression, with the exception that a logistic curve rather than a straight line is fitted to the data. In some cases, neither multiple nor logistic regression was suitable – for example for analysing the amount of sickness absence taken, which for the majority of people was nothing or very little but for a small number of cases was very high. For this analysis Poisson or negative binomial models were used.

In all these approaches, the first step is for each characteristic to be tested in turn to see if it is significantly associated with the outcome (e.g. passed a recruitment stage or not). By significant, we mean that a staff characteristic accounted for an unusually high proportion of the variation seen in the dependent variable. For example, to see if age was a significant factor as to whether someone had passed the interview stage. In this case we would say something was successful or significant in "explaining the variation", to mean that if you knew the characteristic of the staff member, you would have a better chance of predicting the outcome (for example if you knew the age, you would also know something about the likely interview outcome). The starting assumption was that prior knowledge of someone's gender, race, age etc should not enable the model to predict whether they were more likely to have received the highest performance rating or were interviewed etc. Again, as with the univariate approach, significance does not necessarily equate to bias but gives the relative likelihood of it occurring.

The next step in the modelling process was to include the characteristic that explained the majority of the remaining variation after taking account of the first variable. This step was repeated until the variables outside the model could explain no further variation.

Generally, an outcome could not simply be explained by a single characteristic. Often, it was several characteristics together that were important. For example, age, gender, and race were quite often found to be a powerful combination. A major advantage of the multivariate approach, compared with univariate, is that it is easier to see the relative importance of the characteristics.

There was an element of judgment involved in deciding which variables to include. In some cases, variables were highly correlated, e.g. gender and full-time equivalence: females were more likely to work part time than males. Where both were statistically significant and improved the amount of variation that could be explained, both were included.

B.2 Univariate methods - Chi-squared and Proportions tests

These tests were employed to test whether the proportion of staff by each diversity grouping was significantly different from that found within the local working-age population and were used where further investigation was needed of staff age combined with other diversity characteristics. They were also used to investigate recruitment to check if the proportion of candidates by each diversity grouping was significantly different from that of the local working-age population.

The results of these statistical tests give an indication of whether the pattern observed in the data was “significantly different from what would have been expected” or conversely whether any difference in proportions could be explained by natural variation.

For example, if there had been 100 applicants, 30 of whom were male, and the local working-age population was 50% male and 50% female, the tests would tell you whether the group was statistically different from any random sample of 100 from the working-age population.

For these tests we used the “99% confidence level”. This means that if we reported a difference as being significant it meant there was only a 1% likelihood that the difference could have occurred purely by chance. Occasionally, we have reported on differences that were significant at the 95% level – i.e. a 5% likelihood that the differences would have occurred by chance. These were included to improve the robustness of reporting by giving a more complete interpretation where omission of these results could otherwise have been misleading.

A certain amount of variation is expected, even with completely random samples, and so it should not be assumed that something that is statistically significant indicates that there is a bias – the level of significance only indicates the likelihood of something occurring. For example, a significant result at the 99% level would indicate something which is more unusual than something that is only significant at the 95% level.

As there are several characteristics to be tested, several univariate tests had to be conducted. One of the drawbacks of multiple univariate testing is that the more tests that are undertaken the higher the probability of finding false significant results. To reduce this risk, we have used the Bonferroni adjustment to the significance levels.

A further drawback with univariate approaches is that they do not take into account all the other factors simultaneously. In practice an individual staff member has several characteristics: their gender, race, working pattern etc. In looking at only one of these characteristics at a time (for example in relation to performance), the effect of another characteristic is not taken into account and results can be misleading. It is possible to use multi-dimensional contingency tables for chi-squared tests, but the interpretation of the results can be difficult.

It is still, however, an appropriate approach in many circumstances – particularly when the group should be reasonably comparable with the rest of the population, but where possible we are moving away from these approaches.

B.3 Trend analysis

Logistic regression was used to identify trends in the data. This regression included all staff for all years as data points and was performed on gender, race, and disability data. The dependent variable was a binary (0/1) identifying whether or not each staff member belonged to the characteristic that was being analysed (e.g. female, unknown disability status etc.). Year was used as the only explanatory variable, i.e. the regression tried to model the staff characteristics based only on year. If year was a strong predictor of a staff characteristic then this meant there was a significant trend.

For example, if year had a significant positive coefficient for a characteristic then this would mean that the chances of staff having that characteristic significantly increased with time i.e. there was a significant positive trend for that characteristic.

This analysis was univariate – each characteristic was analysed separately and year was the only explanatory variable included. This means that the analysis does not account for relationships between the different characteristics.