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Equality Monitoring 2013/14 Technical Annex

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In House Analytical Consultancy

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Chapter 1: Introduction

This report is the technical annex to the 2013/14 Equality Monitoring reports. It contains notes on the data used in the reports and describes the analytical methodology.

1.1 Equality Monitoring

The Equality Monitoring reports contain key findings from the analyses of the diversity of DfT staff, recruits and leavers for 2013/14.

The aims of the analysis were to:

- summarise the diversity characteristics of staff and applicants;
- compare the diversity of staff with the diversity of local working-age populations;
- identify differences between diversity groups within DfT; and
- highlight any changes since previous years.

For 2013/14, there are 7 reports covering the central department, DfT(c), and each of the executive agencies:

- Driver and Vehicle Licensing Agency (DVLA);
- Driving Standards Agency (DSA) and the Vehicle and Operator Services Agency (VOSA) – now both part of the Driver and Vehicle Standards Agency;
- Highways Agency (HA);
- Maritime and Coastguard Agency (MCA); and
- Vehicle Certification Agency (VCA).

In addition there is an overall report summarising the results for the entire department.

1.2 Analysis and reporting

The analysis considered the following areas of diversity:

- Gender
- Race
- Disability
- Age
- Working pattern
- Sexual orientation

- Religion and belief

And for the following datasets:

- Staff in post
- Recruitment
- Cessations
- Performance management reports
- Learning and development
- Disciplinary cases
- Grievance cases
- Sickness absence

It also gives information about maternity leavers and returners.

Results described in the reports are based on the outcomes of statistical tests. These tests are used to identify statistically significant differences between groups – that is, differences larger than the likely range of natural variation. In general, the reports contain results that were significant at the 99% level.

1.3 Data coverage

For the purposes of these reports, staff in the Senior Civil Service are included within the analysis for the central department, DfT(c).

Staff on long-term leave (for instance long term sickness absence secondments, and career breaks) are not included in the analysis, and nor are staff who are not civil servants (e.g. consultants, temporary administrators etc.).

Staff on maternity leave are included in the staff in post dataset for the first time this year, although excluded from the training and sickness absence analysis.

1.4 Declaration Rates

Data on staff gender, age and pay band are held for each member of staff, but data on disability, race, sexual orientation and religion/belief are voluntarily provided. As a result, and because staff may be unwilling to provide this information, these data often have significant numbers of unknowns or undeclared statuses and subsequently analysis was not always possible.

In these reports, staff who have actively declared that they “prefer not to say” have been classified as having an unknown status.

Declaration rates are tabulated in each summary report.

High declaration rates are important for robust analysis and results that can be confidently extrapolated to all staff; where there are large proportions of unknowns in the

data (either “prefer not to say” or undeclared), if these non-respondents are not representative of all staff, we may introduce bias into the results. For example, a systematic bias may be introduced by the fact that new staff may not have declared their race or disability status yet, and these new staff may also be more likely to be younger, or in lower pay bands; a behavioural bias may be introduced by staff who prefer not to declare any diversity characteristics.

Remarks on data quality are included within each summary report.

Chapter 2: Notes on data

2.1 Working-age populations

2.2 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.

Data sources

The UK population data at Local Authority[1] level is from the **Annual Population Survey (APS).** This survey is a combined survey of households in Great Britain, 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. In previous years, data for Northern Ireland was taken from the **Northern Ireland Labour Force Survey (NI LFS)**; however, this year, this data was also available as a part of the APS dataset.

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 2013/14 Equality Monitoring reports was based on the one year period October 2012 - September 2013, and downloaded from www.nomisweb.co.uk ("Nomis") on 6th June 2014.

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

[2] Further information on the survey can be found at http://www.ons.gov.uk/ons/guide-method/method-quality/specific/labour-market/labour-market-statistics/index.html

Population

Population data at local authority level from the APS was combined with **mid-year** (30 June) **population estimates** for 2012 – the most recent year available. 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 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).

Disability status

Data on disability in the population is no longer available from the APS. The data now collected refers to long-term health conditions only, which means that it is not comparable with staff disability data. As a result, we no longer include this comparison in the analysis.

Race

APS data was 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 BME category.

2.3 Sickness absence data

For DfT(c) and all agencies, data was available on the number of days of recorded sickness absence for each member of staff, with one record per incidence.

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.

[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.

Chapter 3: 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.

3.1 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 data that was analysed had a binary (0/1) result, for example, was in a pay band 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 be part-time than males. Where both were statistically significant and improved the amount of variation that could be explained, both were included.

3.2 Univariate methods - Chi-squared and Proportions tests

These tests were employed where further investigation was needed of staff age combined with other diversity characteristics. Additionally, the univariate approach was the primary approach used for analysing whether the proportion of job applicants 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. We have also sometimes reported on differences that were significant at the 95% level – i.e. a 5% likelihood that the differences would have occurred by chance.

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 of 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.