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Towards an integrated census-administrative data approach to item-level imputation for the 2021 UK Census

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Abstract

In preparation for 2021 UK Census the ONS has committed to an extensive research programme exploring how linked administrative data can be used to support conventional statistical processes. Item-level edit and imputation (E&I) will play an important role in adjusting the 2021 Census database. However, uncertainty associated with the accuracy and quality of available administrative data renders the efficacy of an integrated census-administrative data approach to E&I unclear. Current constraints that dictate an anonymised 'hash-key' approach to record linkage to ensure confidentiality add to that uncertainty. Here, we provide preliminary results from a simulation study comparing the predictive and distributional accuracy of the conventional E&I strategy implemented in CANCEIS for the 2011 UK Census to that of an integrated approach using synthetic administrative data with systematically increasing error as auxiliary information. In this initial phase of research we focus on imputing single year of age. The aim of the study is to gain insight into whether auxiliary information from admin data can improve imputation estimates and where the different strategies fall on a continuum of accuracy.

Key words: Census, Imputation, Administrative data, Canceis

1. Introduction

Adjusting census data for item-level inconsistencies and non-response (from here on referred to as imputation) is an important part of census data processing. The 2011 UK Census imputation strategy was a modularised donor-based approach implemented in CANCEIS (Aldrich and Rogers, 2012; Wardman and Rogers, 2012; Wardman et al., 2014).

In CANCEIS, the variables within a module, along with other auxiliary information, serve as matching variables representing the underlying imputation model. A Nearest Neighbour algorithm constructs a pool of potential donors statistically similar to the record being imputed based on available data in the matching variable set. From that pool, the donor that supplies the imputed value is chosen randomly from a set of near minimum change imputation actions (NMCIAs) (Bankier, 1991; 2000; Bankier et al., 1999; Bankier et al., 2001; Canceis, 2009; Winkler and Chen 2001). This strategy provides point and variance estimates of the distribution of the missing data conditioned by the underlying imputation model (from here on referred to as imputation estimates).

Following a detailed research programme after completion of the 2011 Census, the National Statistician recommended a predominantly online UK Census in 2021, supplemented by the use of administrative data. This was approved by the UK Government in July 2014. The ONS is now fully committed to the development of a different kind of Census in 2021. Exploring the impact that administrative data may have on the accuracy of imputation estimates is therefore an important facet of that commitment.

Blum (2006) describes a number of mechanisms by which administrative records can aid the imputation process. These include cold-deck imputation, improving model specification, and continuous quality assurance. The first of these, cold-deck imputation, carries a risk that observed census data could be changed on the basis of inconsistent values obtained from an external administrative source. Given this risk and the uncertainty surrounding both the quality of available administrative sources and the linkage mechanism, our initial research has focused on the use of linked administrative data as auxiliary information within the conventional hot-deck approach already employed by

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ONS. There is comparatively little research available in this area since research tends to focus on using admin data to avoid the need for hot deck imputation (e.g. Farber et al., 2005).

The aim of the research was to determine whether linked administrative data could improve the accuracy of imputation estimates for age, what an improvement actually looks like, and to gain some insight into where different strategies fall on a continuum of accuracy, with a view to eventually establishing some general principles for the use and evaluation of administrative sources in the 2021 UK Census. Age was used because this is a key census variable and is known to be of generally high quality in a number of admin datasets, making it an ideal candidate for preliminary investigations.

Here we present findings of research based on 2011 UK Census data, which evaluated the differences between imputation estimates obtained using a donor based imputation strategy that included synthetic administrative data as auxiliary information in the form of an 'admin age' variable linked to each census record, compared with the conventional approach as used for the 2011 UK Census.

The first phase of the analysis focuses on the predictive and distributional accuracy (Chambers, 2001) of the imputation estimates for one 'typical' Census delivery group that had age randomly perturbed for 5% of records and was imputed under the following conditions: no administrative data (2011 Census approach), exact administrative data, administrative data with +/-3 years error, administrative data with +/-6 years error, administrative data with +/-12 years error.

Demographic data for households containing 1 to 6 people were used, with the age variable imputed using the 2011 UK Census imputation model implemented in CANCEIS, which included the matching variables of: relationship to household person 1; sex; marital status; activity last week; student indicator, term-time address indicator; country of birth indicator; 'hard to count' rating; as well as the additional matching variable of 'admin age' provided by the synthetic administrative sources, with its weight set to equal that used for age in the 2011 Census. Admin age was set to equal the true census age for all clean records.

The second phase of the study involved deriving error distributions for age from real administrative datasets by matching them to 2011 Census data (assumed to represent the true age) by forename, surname, sex and postal code. These error distributions were then used to create additional synthetic admin age variables which were used to impute the perturbed dataset, as above, in order to determine where real administrative datasets might fall on the continuum of error established in phase 1.

2. Results & Discussion

2.1 Predictive accuracy

Figures 2.1-1 to 2.1-5 illustrate the distributions of the error in imputed age compared with the true age for each of the experimental conditions, based on all potential donors.

Figure 2.1-1.
Exact administrative data condition

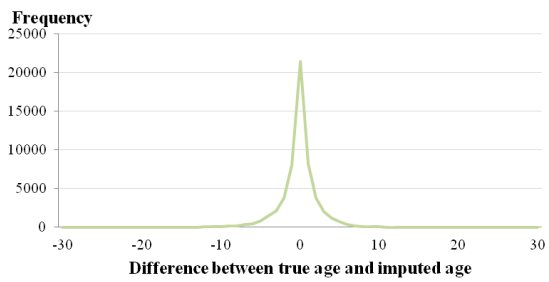


Figure 2.1-2.
No administrative data condition

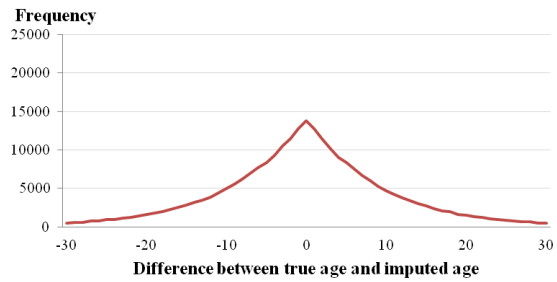


Figure 2.3-3.
+/- 3 years administrative data error condition

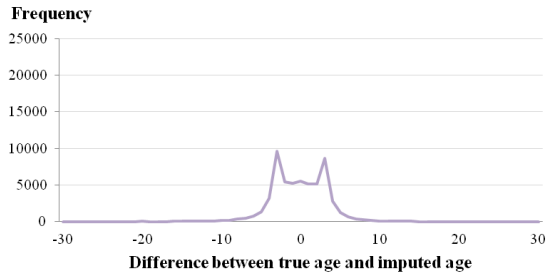


Figure 2.4-4.
+/- 6 years administrative data error condition

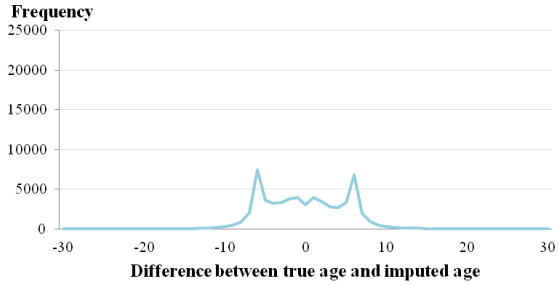
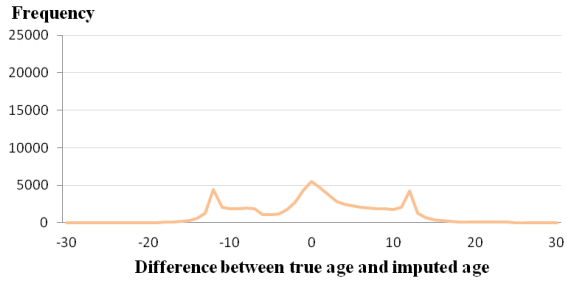


Figure 2.5-5.
+/- 12 years administrative data error condition



The exact administrative data condition clearly performed better than the no administrative data condition, with errors centred around zero but with a much lower standard deviation (3.17, compared with 11.89 for the no administrative data condition, see Table 2.1-1). The other administrative data conditions produced non-normal distributions of error, with modes reflecting the level of error in the admin data variable, which is problematic since it means that these conditions were more likely to impute an erroneous value than the correct one.

Table 2.1-1.
Summary statistics for the error in the imputed age compared with the true age for the no admin data and exact admin data conditions

	No admin data			Exact admin data		
	Estimate	95% Confidence limits		Estimate	95% Confidence limits	
Mean	-0.15	-0.19	-0.10	-0.20	-0.22	-0.17
Std Dev	11.77	-	-	3.18	-	-
Variance	138.47	-	-	10.10	-	-

2.2 Distributional accuracy

Recovery of the true age distribution of the perturbed data was also assessed. Table 2.2-1 illustrates summary statistics for the error in the counts by single year of age for each condition.

Table 2.2-1.
Measures of distributional accuracy for each experimental condition

Error	Exact admin data	No admin data	Admin +/-3	Admin +/-6	Admin +/-12
Mean	-0.019	-0.028	-0.086	-0.114	-0.065
Mean 95% CI	-4.40 , 4.36	-4.90 , 4.84	-6.01 , 5.84	-7.99 , 7.76	-6.98 , 6.85
Std Dev	22.43	25.40	30.61	40.71	36.26
SSE	51,294	68,387	97,425	172,354	140,709
RMSE	22.32	25.28	30.46	40.52	36.10
RMSE 95% CI	18.57 , 25.52	21.04 , 28.91	22.99 , 36.43	30.31 , 48.62	30.57 , 40.88

The exact administrative data condition performed better than the no administrative data condition, with a lower mean error by age, lower sum of squared errors and lower root mean squared error, indicating both less absolute error over the whole age distribution and less error for each individual age. The other administrative data conditions on the other hand, had particular difficulty in recovering the true age distribution at the school age/working age boundary between 15 and 16 years old. As table 2.2-2 shows, only 60% of the true number of 16 year olds were imputed for the +/- 6 years error condition, whereas both the no administrative and exact administrative data conditions accurately recovered the true count of 16 year olds.

Table 2.2-2
Post-imputation frequencies of 16 year olds for each experimental condition

	True values		Exact		No admin		Admin +/-3		Admin +/-6		Admin +/-12	
Age	n	% of total	n	% of total	n	% of total	n	% of total	n	% of total	n	% of total
16	368	1.2	372	1.2	375	1.2	267	0.9	215	0.7	348	1.1

This appears to be due to the presence of records with a true age on one side of the school age/working age boundary and an admin age on the other side. The systematic differences between school age and working age records and the CANCEIS parameterisation used in the 2011 Census to maintain these differences meant that, for example, it was difficult for records with a true perturbed age of 10 and an admin age of 16 to match to 16 year old potential donors, but for records with a true age of 16 and an admin age of 22, there was little to prevent a match to 22 year old donors, resulting in a net decrease in 16 year olds compared with the true distribution.

The +/- 12 years error condition performed better than the +/-6 years condition in terms of distributional accuracy, both in terms of absolute error over the whole distribution and at the school age/working age boundary. This appears to be because the error in the admin age variable was so great that it could not be matched on closely while maintaining consistency with the observed data, resulting in consistency being prioritised over matching on admin age, meaning that there was a higher chance of recovering the true age distribution. In this situation, therefore, the observed Census data was effectively protected from high levels of error in the administrative data.

2.3 Other measures

Some other key measures of imputation accuracy were also analysed (Table 2.3-1). Administrative data of any quality led to a reduction in the size of the donor pool and restricted the age range of the potential donors to only those that matched the admin age very closely. The +/- 12 years condition restricted the donors less than the other conditions for the reasons stated in section 2.2 – at this level of error it was simply not possible to find donors that matched closely on admin age while maintaining consistency with the observed variables for a large number of records.

As would be expected, the percentage of records that would fail the edit checks if the admin age was directly substituted into the census age increased as the administrative error increased, reaching almost 20% for the +/- 12 years condition. This is important because the observed census data are assumed to be the 'truth' so, if the

administrative data are inconsistent with them, there is a risk that observed data could be changed on the basis of the administrative data if the conventional edit rules are implemented. The fact that the imputation method implemented in CANCEIS is able to protect observed data from inconsistent administrative data is therefore an advantage over a direct substitution method.

Table 2.3-1
Other measures of imputation accuracy

	Exact	Admin +/-3	Admin +/-6	Admin +/-12	No admin
Total size of donor pool	56,077	57,529	59,807	70,068	258,116
Average age range of potential donors (years)	1.0	1.1	1.4	2.5	14.3
Percentage of records failing edit checks if admin age directly substituted into census age	0	3.8	9.1	19.4	N/A

2.4 Phase 2: Error distributions derived from actual administrative datasets

Once the general principles had been established, demonstrating what an improvement on the no admin approach looked like and the level of accuracy in the admin data needed to achieve that, the next phase of research focused on determining how two real admin datasets might perform in this context. This involved firstly analysing the error distributions of two actual administrative datasets, the NHS Patient Register (PR) and the Department for Work and Pensions' Customer Information System (CIS), linked to 2011 Census data by forename, surname, sex and postal code. Where age was observed on the administrative source and the Census, both the PR and CIS datasets had over 98% exact agreement with the Census age, indicating high reliability of the age variable.

These observed error distributions were then used to construct a further set of synthetic administrative datasets, which were used as auxiliary information in imputation of the perturbed dataset, in the same way as with the other synthetic datasets. This allowed the analysis to take place outside the constraints of the secure data environment.

Table 2.4-1 sets out the distributions of the error in the imputed age compared with the true age for the two conditions, compared with the exact administrative data and no administrative data conditions. Predictive accuracy was similar to that of the exact admin condition, which is to be expected given the high reliability of the age variable, clearly indicating that existing admin datasets are potentially able to deliver a substantial improvement on the conventional no admin data strategy.

Table 2.4-1
Summary statistics for the error in the imputed age compared with the true age for the CIS and PR synthetic conditions contrasted with the no admin data and exact admin data conditions

	PR			CIS			Exact admin data			No admin data		
	Estimate	95% CIs		Estimate	95% CIs		Estimate	95% CIs		Estimate	95% CIs	
Mean	0.20	0.17	0.23	0.21	0.18	0.24	-0.2	-0.22	-0.17	-0.15	-0.19	-0.1
Std Dev	3.32	-	-	3.33	-	-	3.18	-	-	11.77	-	-
Variance	11.02	-	-	11.10	-	-	10.10	-	-	138.47	-	-

The distributional accuracy for both conditions was also higher than the no administrative condition, with RMSE figures of 21.7 and 21.4 for the PR and CIS conditions respectively, compared with 25.3 for the no administrative condition.

2.5 General discussion

The results show that it is possible for administrative data to substantially improve the accuracy of imputation estimates for age under certain conditions and that existing administrative datasets appear to be of sufficiently high quality to potentially deliver this improvement. The nearest neighbour minimum change methodology implemented in CANCEIS also ensured that, where the administrative data was so erroneous as to be inconsistent with the observed data, consistency was maintained over matching closely on the admin age variable. This effectively protected the observed census data from high levels of error in the administrative data, demonstrating an advantage over alternative direct substitution methods.

2.6 Next steps

The study assumed perfect linkage and 100% data coverage in order to focus on the effects of error in the administrative data, but this would not be achieved in a real situation so the findings represent a 'best-case' scenario. The final phase of the work will therefore focus on determining the effects of imperfect linkage and less than 100% coverage to allow a full cost-benefit analysis of the method to be carried out in preparation for the 2021 Census.

References

Aldrich, S., Wardman, L., and Rogers, S. (2012), "The practical implementation of the 2011 UK Census imputation methodology", *Conference of European Statisticians, Work Session on Statistical Data Editing*, UNECE.

Bankier, M. (1991), "Alternative method of doing quantitative variable imputation", Statistics Canada Memorandum.

Bankier, M., Lachance, M., and Poirier, P. (1999), "A Generic implementation of the nearest neighbour imputation method". *Proceedings of the Survey Research Methods Section*, American Statistical Association, pp. 548-553.

Bankier, M. (2000), "2001 Canadian Census minimum change donor imputation methodology", *Proceedings of the UNECE Conference of European Statistics*.

Bankier, M., Poirier, P., and Lachance, M. (2001), "Efficient methodology within the Canadian Census edit and imputation system (CANCEIS)", *ASA Joint Statistical Meetings*.

Blum, O. (2006), "Evaluation of editing and imputation supported by administrative records", *Statistical Data Editing Volume 3: Impact on Data Quality*, UNECE, pp300-309.

CANCEIS (2009), "Users Guide V4.5". Social Survey Methods Division, Statistics Canada.

Chambers (2001), "National Statistics Methodological Series Report 28: Evaluation criteria for statistical editing and imputation", Office for National Statistics.

Farber, J., Wagner, D. and Resnick, D (2005), "Using Administrative Records for Imputation in the Decennial Census", *ASA Section on Survey Research Methods*.

Wardman, L., Aldrich, S., and Rogers, S. (2012), "Item imputation of Census data in an automated production environment; advantages, disadvantages and diagnostics", *Conference of European Statisticians, Work Session on Statistical Data Editing*, UNECE.

Wardman, L., Aldrich, S., and Rogers, S. (2014), "2011 Census item edit and imputation process", Office for National Statistics.

Winkler, W., & Chen, B-C. (2001). "Extending the Fellegi-Holt model of statistical data editing", *Research Report Series*, U.S. Census Bureau.