**Statistical Disclosure Control (SDC) for 2021 UK Census**

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1. **Introduction**

This paper reports on progress toward the approach to protect the confidentiality of individual respondents to the 2021 UK Census. The paper builds on previous papers and is an evolving working document as progress is made. This protection is enshrined in law and it is thus work that requires regular updates to UK Census Committee and the National Statistician, who are required to give specific approval. The context of this work involves a reasonable amount of history, lessons learnt from previous censuses, and the satisfaction of an active and vocal user community balanced against the legal requirements of Office for National Statistics (ONS) to protect the confidentiality of individual respondents. The scope of disclosure control for the UK census is wide, but the main focus of most of this paper is on the protection of confidentiality within tabular outputs. We discuss the methods used in past censuses and describe the preferred approach for 2021 Census.

1. **Background**

Statistical disclosure control covers a range of methods to protect individuals, households, businesses and their attributes (characteristics) from identification in published tables (and microdata). There is a large literature base now established on disclosure risk, disclosure control and its methodology, notably Hundepool et al (2012). Box 1 highlights the most common forms of disclosure with tabular outputs.

ONS has legal obligations under the Statistics and Registration Service Act (SRSA, 2007) Section 39, and the Data Protection Act (2018) in this respect, and ONS must also conform to the UK Statistics Authority Code of Practice for Official Statistics (2009) that requires ONS not to reveal the identity or private information about an individual or organisation. The General Data Protection Regulation (GDPR) that came into force in UK on 25 May 2018 reinforces our obligations, both in data release and data handling. More generally, we have a pledge to respondents on the first page of the census form that the information will only be used for statistical purposes, so we must look after and protect the information that is provided to us. If we do not honour our pledge there is a risk that response rates to all our surveys could be adversely affected as could data quality. Moreover, a breach of disclosure could lead to criminal proceedings against an individual who has released or authorised release of personal information, as defined under Section 39 of the SRSA.

The SRSA defines “personal information” as information that identifies a particular person if the identity of that person—

(a) is specified in the information,

(b) can be deduced from the information, or

(c) can be deduced from the information taken together with any other published information.

There are exemptions from the SRSA, through which information can be disclosed, for example where it has already lawfully been made publicly available, is made with consent of the person, or is given only to an approved researcher under licence. Note that it is not a breach under the SRSA to release information that could lead to an identification of an individual, where *private* knowledge is also necessary in order to make that identification.

Table 1. Exemplar disclosure table: Ethnic Group x Health (Males)

Box 1. Types of Disclosure

Identification Disclosure: The ability to recognise or identify oneself (or another respondent) as the 1 individual in a table cell. [See Table 1 and the two cells in Very Bad Health column]

Attribute Disclosure (AD): The ability to learn something new about a respondent (or group of respondents) from a table. This is usually where a row or column only has one non-zero entry. [See Table 1 – All Black males have Fair Health]

Within Group Disclosure: A combination of both Identification and Attribute Disclosure. It is the ability to learn something new about a number of other respondents, where a row or column has contains a 1, and only one other non-zero entry. The respondent represented by the 1 can deduce information about the other group members. [Table 1 – the Asian male with Good Health knows all others have Bad Health]

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Good Health** | **Fair Health** | **Bad Health** | **Very bad Health** | **Total** |
| **White** | 6 | 7 | 3 | 2 | **18** |
| **Mixed** | 2 | 2 | 3 | 1 | **8** |
| **Asian** | 1 | 0 | 5 | 0 | **6** |
| **Black** | 0 | 5 | 0 | 0 | **5** |
| **Other** | 0 | 0 | 0 | 1 | **1** |
| **Total** | **9** | **14** | **11** | **4** | **38** |

In order to remain within the law, the data provider must take account of all reasonable sources that might be used to try and identify an individual. The UK Statistics Authority Code of Practice for Official Statistics (2009) underlines the need for arrangements for confidentiality protection that protect the privacy of individual information but that are not so restrictive as to limit unduly the practical utility of official statistics.

The importance of this work is underlined by the potential sanction within the SRSA: An individual who contravenes the legislation and is convicted, could receive a custodial sentence of up to two years, or a fine, or both. This is a sanction for an individual but a breach would also result in significant reputational damage for ONS, as well as considerable scrutiny from select committees, privacy lobbyists and pressure groups, and the media.

1. **Context – previous censuses**

The 1920 Census Act was the first legislation to mention the confidentiality of respondents in UK censuses. However, the understanding of the intricacies of statistical disclosure (as opposed to the security of the forms and their information) did not result in any specific disclosure control measures until the 1971 Census. Previously, there had been some protection in tables due to many being based on a 10 per cent sample of respondents. The 1991 Census used a method of cell perturbation referred to as Barnardisation, whereby some cells in some small area tables had random noise added or subtracted.

**3.1 2001 Census**

In the 2001 Census, the records on the output database were slightly modified by random record swapping. This means that a sample of households was 'swapped' with similar household records in other geographical areas. The proportion of records swapped was the same in all areas. No account was taken of the protection provided through differential data quality (due to, e.g. different levels of non-response imputation). Further information about the proportion of records swapped cannot be provided as this might compromise confidentiality protection.

Random record swapping had some limitations and the Office for National Statistics (ONS) became increasingly concerned about these. It was felt that it would not be apparent to a person using the census data that any method of disclosure protection had been implemented. There would be a perception that persons and households were identifiable (particularly for a cell count of 1) and the observer might act upon the information as if it were true.

At a late stage (in fact, after all the disclosure control methodology had been agreed and communicated to users) a review was held to decide on the implementation of additional disclosure protection. The decision was to add a post-tabular small cell adjustment (SCA) method. It involved adjusting the values of small cells up or down according to rules that a proportion of the cells with that small value will be adjusted up, while the rest of the cells with that value will be adjusted down. SCA was applied after random record swapping had been carried out on the microdata.

During the process of small cell adjustment:

* a small count appearing in a table cell was adjusted (information on what constitutes a small cell count could not be provided as this may have compromised confidentiality protection)
* totals and sub totals in tables were each calculated as the sum of the adjusted counts so that all tables were internally additive (within tables, totals and sub totals are the sum of the adjusted constituent counts)
* tables were independently adjusted (this means that counts of the same population in two different tables were not necessarily the same)
* tables for higher geographical levels were independently adjusted, and, therefore, were not necessarily the sum of the lower component geographical units
* output was produced from one database, adjusted for estimated undercount, and the tables from this one database provided a consistent picture of this one population.

The fallout from this was considerable. ONS received numerous complaints from users, broadly covering the following:

* The very late decision to implement SCA
* The data looked ‘wrong’ – in that there were no 1s or 2s and published tables were not consistent with each other
* Consultation with users on this had been limited
* Tables still took time to pass through manual table checking, since there was a risk of disclosure by differencing
* The method was not harmonised across UK. SCA was employed for tables using data from England, Wales and Northern Ireland while not for Scotland (who felt that the risk was very low anyway).

In 2005, the Registrars General agreed that small counts (0s, 1s, and 2s) could be included in publicly disseminated census tables for 2011 Census provided that

a) there was sufficient uncertainty as to whether the small cell is a true value had been systematically created; and

b) creating that uncertainty did not significantly damage the data.

By implication, the uncertainty around counts of 0 corresponds to uncertainty of attribute disclosures.

**3.2 Evaluation pre-2011**

The SDC team had previously undertaken a long post-2001 Census evaluation review to assess all possible disclosure control methods that could be used for protecting frequency tables in the (forthcoming) 2011 Census. ONS (2010) describes this evaluation, the first phase of which narrowed down the methods to a short-list of three: record swapping, over-imputation, and an Invariant ABS Cell Perturbation (IACP) method. The IACP method (see Shlomo and Young, 2008) was an extension of the Australian Bureau of Statistics (ABS) approach where controlled noise was added to cell counts in frequency tables.

Users’ uppermost concern was that the tables needed to be additive and consistent. Given these were key issues within the negative feedback from 2001, and that additivity and consistency could not both hold for the IACP, that method was discounted as failing on the mandatory criteria. The remaining two methods, record swapping and over-imputation, were scored against criteria developed by ONS SDC and the UK SDC Working Group, which included membership from both GROS and NISRA. The Group agreed the criteria and relative weights and scored record swapping as slightly better than over-imputation.

1. **Record Swapping – How it Worked in 2011**

Record swapping is now a well-established method of disclosure control in scenarios where large numbers of tables are produced from a single microdata source. The US Census employed this for 1990 to 2010[[1]](#footnote-1) (see Zayatz, 2003) and its strengths and weaknesses outlined in Shlomo et al (2010), prior to the 2011 UK Census. It has been used in non-census collections (see Kim, 2016) but in the UK its use has predominantly been in the last two national censuses. It is occasionally used on a small purposive scale to protect microdata where there are a small number of very unusual records that require protection. The following describes the method’s use within the 2011 UK Census.

Every individual and household were assessed for uniqueness or rarity on the basis of a small number of characteristics (at three levels of geography) and every household given a household risk score. A sample of households was selected for swapping. The chance of being selected in the sample was based largely on the household risk score, so that households with unique or rare characteristics were much more likely to be sampled. Every household had a chance of being swapped. Once selected, another ‘similar’ household was found from another area as a ‘swap’.

The household and its swap were matched on some basic characteristics in order to preserve data quality. These characteristics included household size, so that the numbers of persons and numbers of households in each area were preserved. Households were only swapped within local authorities (LADs) or, in the case of households with very unusual characteristics, with matches in nearby authorities. So there were no households, say, in Cornwall swapped with any in Birmingham.

The precise level of swapping was not disclosed to the public so as not to compromise the level of protection that swapping provides. The level of swapping was lower in areas where non-response and imputation were higher and already provide a degree of protection against disclosure, so the swapping level varied across the UK.

If the level of imputation in an area was high, the level of swapping required was lower than in other areas. We still had to protect the very unusual and more identifiable persons who have completed and returned their census forms, even in the areas with lots of imputed records, so some record swapping was carried out in every area. A consideration for 2021 is that imputation might be improved due to auxiliary information from other sources and so might not provide so much protection.

The swapping methodology was such that every household and every person did have a chance of being swapped, so all cell counts had a degree of uncertainty. Indeed, given that some persons did not respond to the census and some questions were not answered by all, there were also imputed records appearing in the census database and therefore in the cell counts. The combination of imputation and swapping produced some apparent attribute disclosures that were not real, and some cell counts that included imputed and/or swapped records.

People or households with rare or unique characteristics might reasonably expect to be able to see themselves or their household in the data. However, there may be a number of reasons why such a person or their household may not be apparent. There was a very small chance that the information may not have been captured properly (especially in paper responses), but more likely the household was selected for swapping with a household in another area, or that it may have been matched with another household that had been selected for swapping.

No persons or data items were removed from the census data and therefore outputs at national level and high geographies were unaffected by record swapping. The level of non-response and imputation actually had a far greater effect on utility than did record swapping. Care was taken to achieve a balance between disclosure risk and data utility and, because we are targeting records where the risk of disclosure is greatest, most analyses based on larger numbers was not greatly affected.

Note that record swapping was also applied to communal establishment data. 2011 was the first UK Census in which these were subject to pre-tabular disclosure control. The Frend et al (2011) method was somewhat like that for households, where individuals were swapped between communal establishments, with individuals matched on basic demographic characteristics.

1. **Assessment of 2011 Outputs post-record swapping**

**5.1 Assessing Risk in Outputs**

The key issue with assessing disclosure risk was that there was no clearly defined measure of “sufficient uncertainty”. The agreement of how to measure uncertainty and the level to be deemed sufficient was only agreed at an extremely late stage. Meanwhile, the output table definitions and layouts were already in development. Agreement with the National Statistician on the criteria to be used was only achieved at a late stage, these being the minimum proportions

of *real* attribute disclosure (AD) cases that imputation and swapping have protected, and

of *apparent* AD cases (i.e. in the swapped data) that are not real.

An intruder testing exercise (see Spicer et al, 2013) provided empirical assessments and evidence of the level of disclosure risk, a level that was deemed acceptable in satisfying the need for “sufficient uncertainty”. However, the exercise did highlight some areas within the data that appeared to be vulnerable and these were addressed within the output specifications.

The result of this was that every table had to be checked against these criteria. The scale of this requirement was enormous, with around 8 billion cells of data released. The number of tables released for 2011 Census was:

229 Detailed Characteristics tables, for MSOA and above (for some it was LAD and above)

204 Local Characteristics tables, for OA and above

27 Key Statistics tables

75 Quick Statistics tables (univariate), for OA and above

122 various other tables for workday population, workplace population, migrants and others

This total does not include a vast range of origin-destination tables and over 1,000 commissioned and bespoke tables to date, which still require an ongoing SDC resource.

**5.2 User Feedback from 2011**

Though most users of census data appreciate the need for disclosure control to protect confidentiality, the balance between the needs for protection against disclosure risk and for providing sufficient data utility creates a tension between data providers and end users. In commenting on the user needs in relation to this, the user feedback generally covered the following:-

* They liked targeted record swapping as a disclosure control method
* They felt output checking was a bottleneck
* They thought there were “indirect and unintended” consequences of SDC
* Tables were sometimes revised in a way that was not user-friendly
* ONS were perhaps over-cautious in some situations (e.g. with benign tables such as age x sex at the lowest geographies)

SDC processing – record swapping - generally went well and we need to build on good practice from 2011. Tables that failed the criteria in 5.1 were re-designed by collapsing categories or raising the geographic level. Re-design caused a delay in the production of detailed tables and sometimes frustration among some users about how collapsing had been carried out. It is vital that there are early decisions as to the outputs that ONS is prepared to allow, and the user-defined system should help as a catalyst for that.

1. **The 2021 Census**

**6.1 Areas for Improvement for Outputs**

In its phase 3 assessment of the 2011 Census, the UK Statistics Authority spoke to a range of users about their experience of 2011 outputs. Generally, users were positive about the releases and the engagement activities which had been carried out. However, concerns were raised around three aspects of dissemination – accessibility, flexibility and timeliness. These findings were consistent with evaluation work carried out by ONS and the other UK Census offices.

The UK Census Offices are determined to build on what worked in 2011 and address what worked less well.

To help focus priorities, early work looked at a strategy which targeted user concern in the three areas highlighted by UK Statistics Authority:

a. Accessibility – Users reported difficulty in locating specific items, in part compounded by the dissemination approach of publishing a high number of predefined tables.

b. Flexibility – Users reported a desire to create their own outputs and frustration with decisions taken on the level of detail made available.

c. Timeliness – Users expressed disappointment that no substantial improvement had been made in 2011 compared to the release of 2001 Census outputs.

The challenge of satisfying the user community is balanced against the legal obligations to protect against disclosure risk. This balance of risk versus utility is the classic problem for statistical disclosure control.

In looking again at the process of producing outputs, work was carried out to evaluate the most appropriate combination of pre- and post-tabular methods for disclosure control. The favoured method was to consider a combination of targeted record swapping along with a post-tabular cell key method.

Timeliness and flexibility can be addressed through the availability of an on-line table builder, allowing a user to define the table that they require. The level of detail that a user can be allowed is subject to the assessment of disclosure risk that that combination of variables and geography will generate. This has sometimes been referred to as ‘disclosure control on the fly’ but much of the risk assessment has to be carried out prior to the table builder being available. The Table Builder is discussed at length later in this paper (Section 7).

Box 2. Why is record swapping not enough? Why can’t we just release everything?

The basis of the level of doubt is that a sufficient proportion of real attribute disclosures are removed by imputation or swapping, and a sufficient number of apparent attribute disclosures that are introduced by imputation or swapping. The targeting means the most risky records are much more likely to be swapped. Every household has a non-zero probability of being selected for swapping. Therefore, there is a level of doubt as to whether the value of one is real. It may be that a person has been imputed or swapped so as to appear in that cell, or indeed there may have been another person or persons swapped out so as to move from that cell, thus creating the value of one. So one cannot ever be sure that a value of one that they see in a table is really the true value.

However, in particular cases where tables (or parts of tables) are sparse, it is difficult to protect all the vulnerable cells with an acceptable rate of record swapping (see Table 2). The level of swapping must be kept low enough to avoid significant loss of utility, but it would need a much higher swap rate than would be desirable in order to sufficiently protect the very high numbers of small cells and attribute disclosures. We also have a duty to protect against the perception of disclosure, the perception that we are not properly protecting the data supplied to us by individual respondents. The trade off in maintaining the utility of outputs is therefore to restrict the breakdowns of variables and/or the numbers of cells.

Table 2. Exemplar sparse table: Tenure x Ethnic Group

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | White | Mixed | Black | Asian | Other | Total |
| Owned outright | 22 | 1 | 0 | 1 | 0 | 24 |
| Owned with mortgage or loan | 34 | 3 | 0 | 1 | 0 | 38 |
| Shared ownership | 1 | 0 | 0 | 0 | 0 | 1 |
| Social rented from council | 19 | 0 | 1 | 0 | 1 | 21 |
| Other social rented | 6 | 0 | 0 | 0 | 0 | 6 |
| Private landlord | 16 | 0 | 0 | 3 | 0 | 19 |
| Employer of a household member | 0 | 0 | 1 | 0 | 0 | 1 |
| Relative or friend of household member | 1 | 0 | 0 | 0 | 0 | 1 |
| Other | 0 | 0 | 0 | 0 | 0 | 0 |
| Live rent free | 1 | 0 | 1 | 0 | 0 | 2 |
| Total | 100 | 4 | 3 | 5 | 1 | 113 |

**6.2 Changing landscape**

After the 2011 Census, feedback was that users generally liked the record swapping method, but the key demands for a future census were for flexibility, accessibility and timeliness, above additivity and consistency. At the same time, changes in the data environment, a greater public awareness and concern over data privacy and security, and more computing power for more sophisticated intruders has necessitated consideration of improved methods for assessment and protection of risk.

On the utility side, the need was for a disclosure control method that would allow a table builder with users able to interact by requesting combinations of census variables to form tables. The potential methods were:

* As is 2011 (targeted record swapping)
* More (a higher level of) record swapping
* ABS Cell Key method
* Record swapping plus ‘light touch’ cell key perturbation
* Small cell adjustment

**6.3 Differential Privacy**

An emerging approach to protecting individuals within datasets is that of differential privacy. The overriding principle is that “the risk to one’s privacy …. should not substantially increase as a result of participating in a statistical database” (Dwork, 2006). Effectively, one should not be able to learn anything about an individual by differencing between outputs from a database containing the individual and outputs from the same database that does not contain the individual. Put differently, differential privacy hides the presence of an individual in the database from data users by making two output distributions, one with and the other without an individual, be computationally indistinguishable (for all individuals) (Lee and Clifton, 2011).

Of course, the risk here is not zero, but should be very low. How low depends on the risk appetite of the data provider and the approach is characterised by the parameter Ɛ to quantify the privacy risk posed by releasing the outputs. Ɛ reflects the relative difference between the probabilities of receiving the same outcome from the two different datasets, one with and one without the individual subject. A release that satisfies the criterion of being bounded above by Ɛ is said to be Ɛ-differentially private.

Differential privacy is not a method but an approach. Differential privacy typically uses an output perturbation technique which adds random noise to the outputs. The selection of Ɛ determines the level/distribution of that noise, which may be arbitrary and very much driven by the level of risk aversion of the data provider. As in traditional disclosure control approaches, the goal is to find a good balance between reducing risk and maintaining usefulness of the end use release. The field of differential privacy is still young and a too stringent choice of Ɛ generally eliminates any useful information. However, there are some specific use cases where differential privacy can be used without any significant loss in utility (Cabot, 2018).

The approach is mathematically neat but mostly still at the theoretical and academic stage. The use is not yet developed for general-purpose practical applications or for an NSI yet to use in anger in a national census. US Census Bureau are aiming to use for 2020 US Census and Garfinkel et al (2018) provide a useful discussion on issues encountered towards that aim. With differential privacy still in its infancy, the tendency is to over-protect the data taking a “worst case” scenario, though this is intentional to design against a potentially sophisticated intruder taking advantage of *any* vulnerabilities that may lie within the outputs. Rinott et al (2018) discusses the use of differential privacy in protecting frequency tables, in particular the issues in assessing the appropriate level and distribution of noise.

Some traditional SDC methods have elements of differential privacy in them, though perhaps not employed in such a formal manner. The level of noise added by perturbative methods is not normally parameterised as formally as in a differential privacy approach. Moreover, bearing in mind the main protection of record swapping in the 2021 UK Census case, there are useful aspects of differential privacy that can be considered. In particular, it is helpful in assessing the level of parameterisation needed in the cell key method, discussed in section 6.4, which is effectively a flavour of the differential privacy approach.

UK Census Committee (UKCC) advised that development work should concentrate on the option of record swapping plus ‘light touch’ cell key perturbation.

**6.3.1 ONS Differential Privacy pilot**

Differential privacy is a strong privacy guarantee that a single respondent’s information makes measurably little difference to the final outputs. In practice this is because their input is outweighed by noise addition. Differential privacy can be achieved in a number of ways, and the most common is the addition of noise from a Laplace distribution. Differential privacy has a single parameter ε to indicate the level of protection, where lower values of ε indicate more protection. For protection ε on a table one can apply noise from Laplace(scale=1/ε). The US Census Bureau have adopted differential privacy for Census 2020, to protect against the risk of reconstruction attacks.

A differential privacy pilot was run on mortality data within the ONS Secure Research Service. Outputs were produced using two different differential privacy approaches. The first is to directly add noise to frequency table counts for a range of tables and ε values. This has two major differences to cell-key perturbation (also a post-tabular noise method):

* ε-privacy budget: in the differential privacy paradigm, each output is considered to contribute to the overall disclosure risk. The total protection ε for a set of outputs is the total of ε values used for each table. For a total budget of ε, 10 frequency tables would need to be given Laplace (1/ (ε/10)) each. This is better suited to releases with a limited number of outputs, known ahead of time. Further releases of data increase the amount of budget used and weakens the privacy guarantee.
* Perturbing zeros: to meet the differential privacy standard, zero cells need to be treated like all other cells. This results in negative noise given to zero cells, leading to apparent negative cell counts. Post processing is allowed to be used to correct this but leaves other bias issues to be dealt with.

The second, ‘top-down’ method creates a set of microdata from post-noise frequency tables. The microdata as a whole is within the ε budget so many outputs can be produced. The perturbation of zeros and small counts cause a significant bias issue in our implementation. This method would be much more difficult to apply for a large number of variables, which would make the process computationally intensive, but it would also be difficult for noise to affect the counts without overpowering them (imagine adding noise to a table that is only zeros and ones).

**6.4 The ‘Cell Key’ Method**

A key part of the work towards 2021 involved assessing the ‘cell key’ method developed and used at the ABS. The method is based on an algorithm which applies a pre-defined level of perturbation to cells in each table. The same perturbation is applied to every instance of that cell. In a similar way to record swapping, the precise level of perturbation would need to be set as part of the development of methods (Fraser and Wooton, 2005).

In the lead up to 2011 UK Census, ONS had considered a variant of the ABS method (Shlomo and Young, 2008) but had ultimately rejected it on the basis that it would give rise to small amounts of inconsistency between cell counts and their breakdowns. The inconsistencies would have been small but users had previously expressed their strong desire for additivity and consistency as the most important criteria for 2011 outputs.

The simplest version of the method is demonstrated in Box 3. Every record within the microdata is assigned a record key, which is a random number across a prescribed range, typically 0-99[[2]](#footnote-2). The random numbers are uniformly distributed. When frequency tables are constructed, each cell is a count of the number of respondents, and the cell key is calculated by summing their record keys. The combination of cell value and cell key is then read from a previously constructed look-up table (termed here as the ptable) to decide the amount of perturbation that should be used.

Where the same cell (or same combination of respondents) appears in different tables, the perturbation will be the same, due to the same cell value and cell key.

The main advantages of the method are that it allows tables to be protected without the need for a case-by-case assessment of disclosure risk and that a greater combination of outputs can be produced. This has potential for a step change in the flexibility of outputs. As demonstrated by ABS, the method can be used to systematically protect user defined outputs. The main disadvantage is that although the same cell of data is consistent in all outputs, there may be differences between that cell and the equivalent aggregation of other cells. Hence a cell containing the number of 20-24 year olds in an area will always be the same across different tables but this may not be the same as the sum of 20, 21, 22, 23 and 24 year olds in other tables.

There can be an additional protection within the method whereby all 1s and 2s are perturbed, either to 0s or cells of at least size 3. However, this would resonate of the small cell adjustment method in 2001 UK Census, a method that was deeply unpopular with users. The method also only partly protected the outputs due to a residual risk of disclosure by differencing. A better intention for ONS would be to maintain the *appearance* of 1s and 2s in output tables, even though many will have been perturbed. It is to be noted that the intended method for ONS SDC in 2021 is for a light touch cell key perturbation to support the primary method of record swapping.

The light touch of the cell key method should mean that the inconsistencies between different tables are kept to a minimum. It should also mean that most outputs should be available extremely quickly, and not subject to manual case by case checking, as had been the case in 2011. Though there will be differences (inconsistencies) between cell counts and the counts of breakdowns of these cells, the cell perturbation should offer considerable protection against disclosure by differencing. Indeed, when the ABS method was originally proposed, it was principally as a method for protecting against differencing (Fraser and Wooton, 2005).

Disclosure by differencing occurs when two or more separate outputs, each of which are ‘safe’ in isolation, can be used in combination to produce a disclosure. For instance, a table based on ‘all adults aged 16-64’ could be compared with an identical one based on ‘all adults aged 16-65’, such that the subtraction of counts from the former from those of the latter would give a table relating just to the likely small number of those adults aged 65. Differencing is most likely to occur due to either the use of marginally different breakdowns of the same variable, different population bases, or the use of overlapping geographies giving rise to geographic ‘slivers’. Where noise has been added through the cell key method, the difference between two counts has greater uncertainty, since either, both or neither of the counts may have been perturbed. Therefore, some of the apparent differences may not be real, and it is important that there are sufficient metadata so that users and even potential intruders are aware of this potential.

Box 3. Example of the Cell Key Method



**6.5 Perturbing Zeros**

An option to add uncertainty into any claims of disclosure – notwithstanding the record swapping that has taken place previously – is to allow perturbation of cell counts of zero.

In order to perturb cells with counts of zero there are several differences from perturbing populated cells that need to be dealt with:

* i) For the standard perturbation, the value of perturbation is determined by the cell value, and the ‘cell key’ which is generated using the record keys of all individuals within the cell. The zero cells contain no records (and therefore no record keys) with which to do this.
* ii) Other cell values receive noise that is both positive and negative, ensuring it has an expected value of zero, but since negative counts are naturally not allowed, any perturbation of a zero must be positive, to a one or two, say. This would introduce an upwards bias to the table population by only increasing the cell counts.
* iii) For sparser tables at lower geographies especially, the zero cells make up the vast majority of counts. This means that the frequency table will be sensitive to even low rates of perturbation.
* iv) Some of the cells will be structural zeros, cells which represent a combination of characteristics that are considered highly unlikely to occur, if not impossible. These cells must be kept as zero to avoid inconsistencies, confusion, and user perception of low quality data.

The first issue can be overcome by distinguishing between the zero cells using the characteristics of the cell itself rather than the records belonging to it. We assign a random number to each category of each variable and use the modulo sum of these random numbers to produce a random and uniformly distributed category cell key, in a very similar way to the cell key. This category cell key can be used to make a random selection of cells to perturb. Applying a category cell key in this way ensures zero cells are perturbed more consistently across tables the same way the cell key method ensures consistency when the same cell appears in different tables. This repeatability is obviously preferable to simply selecting random zeros within a table to be perturbed.

The ptable is unbiased in that, for each non-zero count, equal numbers of cell counts are perturbed up as down. In order to provide the protection of perturbing some zeros, we also need to deliberately perturb some additional counts down to zero, and so preserve this unbiasedness. To decide how many additional cell counts of one are perturbed down to zero, there is an algorithm that looks at the numbers of cell counts of zero and one, both at this and higher geographies, to consider the level of disclosure risk present before this extra perturbation. Then the requisite numbers of cell counts of one are perturbed down to zero and an equal number of zero cells are perturbed up to one, using the category cell keys.

Structural zeros (see next section) should not be perturbed, and so are given an arbitrarily low category cell key (say 0.001[[3]](#footnote-3)). The cell counts are perturbed to one for the desired number of zero cells with the highest category cell keys. This avoids any population in a cell that has a structural zero count.

**6.6 Determining structural zeros**

Although structural zeros are well defined by the edit constraints, implementing all constraints in the code would be lengthy, slow to run, and leave margin for human error. Cells that defied any constraints are checked for in all tables (whether or not the edit is relevant) and conditions defined on several variable breakdowns, and potentially millions of possible combinations of categories in different variables. A suggested alternative is to use the cell counts from elsewhere in the table to signal whether the combination should be considered as highly unlikely or impossible. This method allows or disallows the perturbation of a zero cell based on whether that combination has occurred in a different geographical area. This method creates the frequency table at a higher geography (perhaps regional or national level) and assigns a low category cell key to all cells that are zero at that higher geography, i.e. have not been observed elsewhere in the region/country.

If a combination of characteristics has occurred elsewhere in the table, it is allowed to reoccur in another area. If a combination has not been observed elsewhere this is prevented from occurring as a result of perturbation to a zero cell count. This will cover all cells disallowed by the edit constraints (since they should have been edited out of the microdata before this stage) and other combinations that were feasible but were not observed in any geography (very unlikely to occur, e.g. a 90 year old student).

The main difference caused by this change to the method is that it prevents perturbation of zeros for combinations of attributes that have never even occurred anywhere else, even if they were not explicitly ruled out by edit constraints. Conversely, it would allow perturbation to occur in a cell, if this attribute combination had occurred anywhere in the data. The method thus allows attribute combinations to happen as long as they remain ‘possible if unlikely’.

Note that this change does not affect the rate of perturbation or how many zeros are perturbed, only the selection of which zero cells are disallowed/excluded from perturbation. In many cases this change has little impact as a zero cell is initially unlikely to be perturbed. Equally, the cells that would be chosen for perturbation are unlikely to be structural zeros to begin with. An example of the use of the algorithm for perturbing zeros is outlined in Box 4.

Box 4. Exemplar use of the algorithm for perturbing zeros (Table = Age x Marital Status)

Step 1. Assign category keys to variables.

|  |  |
| --- | --- |
| Age | Category key |
| 0-15 | 0.924 |
| 16-24 | 0.864 |
| 25-34 | 0.336 |
| … |  |
| Marital Status | Category key |
| Single | 0.484 |
| Married | 0.732 |
| Divorced | 0.111 |

Step 2. For each ‘zero’ cell, calculate Category Cell Key = sum of category keys for that cell

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Age by Marital Status** | Single | Married | Divorced | Category | Category Cell Key |
| 0-15 | 14 | 0 | **0** | Age: 0-15 | 0.924 |
| 16-24 | 8 | 4 | 0 | Marital Status: Divorced | 0.111 |
| … | … | … | … | Sum Category-key = 1.035 | | |
|  |  |  |  | Cell key = 1.035 mod 1 = 0.035 | | |

Step 3. Where cell count is 0 even at higher geography, assume ‘structural zero’ and assign Category Cell Key as insignificant low value (in this case of ‘0-15 Divorced’ replace 0.035 by 0.001).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Age | Marital Status | Category Cell Key | Cell value | Higher geog cell value |
| 0-15 | Single | . | 14 | 223 |
| 0-15 | Married | 0.001 | 0 | 0 |
| 0-15 | Divorced | 0.001 | 0 | 0 |
| 16-24 | Single | . | 8 | 151 |
| 16-24 | Married | . | 4 | 77 |
| 16-24 | Divorced | 0.975 | 0 | 2 |
| … | … |  |  |  |

Step 4. Calculate how many zero cells need to be perturbed. Perturb those with the higher or highest Category Cell Keys.

|  |  |  |  |
| --- | --- | --- | --- |
| Age | Marital Status | Category Cell Key | Cell value |
| 0-15 | Single | . | 14 |
| 0-15 | Married | 0.001 | 0 |
| 0-15 | Divorced | 0.001 | 0 |
| 16-24 | Single | . | 8 |
| 16-24 | Married | . | 4 |
| 16-24 | Divorced | 0.975 | 0 🡪 1 |
| … | … |  |  |

**6.7 Complementary Methods**

Broadly speaking, the two methods complement each other, serving different purposes, to make it much more difficult to identify a named individual person or household.

**Record swapping** – purpose to protect the very unusual individuals / households

**Cell Key Method** – purpose to protect against differencing between tables

If we used **record swapping** only:

* Likely to need higher swap rates
* Some possibility of linking between tables to build up an individual record (which would be a much greater risk when using a table builder, as opposed to just pre-canned tables)
* No protection against disclosure by differencing
* Utility at local authority / delivery group – or at the highest geographic level at which swapping takes place – would be unaffected since the estimates would remain unchanged
* Utility at lower geographies would be more severely affected though the level of swapping is kept as low as possible

If we used the **cell key method** only:

* Likely to need higher level of perturbation
* Still some risk, where a characteristic of is very unusual, of linking between tables to build up an individual record
* Likelihood of utility being severely affected, with many more (and larger) inconsistencies between the same totals where broken down in different ways

There are two additional important nuances:

* **Perturbation of zeros** that provides uncertainty as to whether a small count (particularly a count of 1) represents a record, real, imputed, swapped or otherwise. Because a cell count of zero has no records attached to it, there are no record keys, so this is a separate process that perturbs a small number of zeros to non-zero counts, while ensuring that these are not structural zeros.
* **Disclosure checks** – (see 7.2) after record swapping and the cell key method have been applied, a final (automated) check takes place. This assesses tables against the criteria by which combinations of variables are deemed suitable for publication. The process protects against very sparse tables that might help build up an individual record, even if it might not be real (imputed) or in the right location (swapped), and against any perception that ONS is not protecting the data. The checks allow the table to be provided for those geographic areas where the risk would be sufficiently low, rather than the more traditional disallowing of the whole table where the overall risk is higher.

While the resultant risk of disclosure is not zero after applying both the Record Swapping and Cell Key method, a disclosure of information on an individual person or household would require an intruder to break two methods, each of which introduces uncertainty into any apparent disclosures in published outputs. The use of the two approaches combined therefore provides additional protection over and above the protection provided by each method individually.

1. **Flexible Table Builder**

The intention is to have a facility for users to build their own bespoke tables, selecting the desired combination of variables and choice of breakdowns within them. There will be some restriction on these, and it is a moot point as to how ‘flexible’ one might consider that to be, given that there is a finite (though extremely large) number of tables that can be built. The Table Builder will be dynamic in the sense that tables will be assessed for disclosure risk at the time of request – rather than as one of a previously defined list to be assessed prior to the release of the Table Builder. That said, there will be a number of ‘pre-canned’ combinations of variables that will be available as the user requests popular tables.

**7.1 Risks – recurrent unique combinations**

Blanchard (2019) provides a nice discussion of the general issues related to using table builders. In particular, she highlights key risks of univariate uniques, disclosure by differencing, ensuring sufficient disclosure protection, and the effect on microdata releases. Univariate uniques allow a single record to be constructed but even low counts can be risky here.

In a table builder scenario, frequency tables could in some cases be collated to learn several attributes about individuals. The simplest case is where an individual is unique on one or a small number of variables and repeated similar requests could expose the whole of an individual record. For example, if there is only one person in an area with a specific attribute (a unique value for variable A), then requests of A x B, A x C, A x D, etc. will build up the census record relating to one individual – the respondent who is unique in the category within variable A. This risk can occur at lower geographies but records potentially exposed to this have been heavily targeted for record swapping.

Consider a table: V1\*V2\*V3, which passes the disclosure checks at LAD level. This table includes a set of cells that are ‘1’s.

Attempt to build tables: V1\*V2\*V3\* V4

V1\*V2\*V3\* V5

V1\*V2\*V3\* V6… etc

When several of these tables pass, potentially many attributes can be collated (V4, V5, V6…) ‘microdata records can be rebuilt’ on records that are ‘1’.

After considering the swapping, the risk of rebuilding is much greater at high levels of geography, above MSOA/LAD, above the level where the majority of swapping is performed, and so have least protection from swapping.

Some extent of ‘rebuilding’ is possible so long as attribute disclosures can be present in output tables. The disclosure check parameters can be altered to allow a level of rebuilding that is deemed acceptable, e.g. by ensuring that tables have less sparsity, hence fewer cells of ‘1’, or more likely by reducing the number of attribute disclosures that are allowed. More perturbation of ‘1’s could also be considered, though is likely to provide less effective protection.

In a table builder environment with a large number of outputs, software solvers can be used to combine frequency tables into an estimate of the microdata. A random set of microdata is created, then iteratively altered to match the known outputs (tables). This is done by solving a large system of equations that represent the frequency tables. The solution to this system is a ‘best-guess’ of microdata, a microdata set that would produce the same counts for all frequency tables. Releasing more tables allows more accurate reconstruction.

This process is very computationally intensive and has been trialled on a subset of test data. Solving the sets of equations gets much more computationally difficult with increases in the number of people in an area, and when more tables are released.

Cell-key perturbation causes small inconsistencies between tables and means that the system of equations from perturbed frequency tables may well not have a solution. SAT solvers fail when run on perturbed tables, and reconstruction cannot be performed. We must assume that an alternative technology could exist that finds a close approximate solution, and for testing have used unperturbed tables. Approximate solutions will be more complicated to calculate and may be less accurate.

The risk of reconstruction is considered lower than on US Census data, which reports at much smaller geographies, and releases more detail. Larger areas are expected to be reconstructed more accurately. However, reconstruction is not the same as reidentification. A reconstruction of a record is only the first stage towards identifying the individual, requiring sufficient external information to link a named individual with the record. There is an interesting discussion of this and the background to the situation with U.S. census data in Mervis (2019).

This risk is addressed in three ways, (1) targeting record swapping more heavily towards all ‘risky records’, (2) adding noise through the cell key method – see 6.4 - and (3) restricting the tables which users can build. We have termed the latter ‘Business Rules’ or ‘Disclosure Checks’.

Protection for the 2011 Census data concentrated on targeted record swapping. A small number of variables were selected based on being visible, sensitive or likely to be known by friends or associates. Every individual was assessed for disclosure risk by considering whether they were unique on any of those variables at OA, MSOA and LAD level. Any household containing one or more ‘risky’ individuals was deemed a risky household.

Households were selected for swapping from the pool of ‘risky’ households, the proportion swapped in any area based on the prevalence of risky records, the population size, and the level of record imputation. There was also a smaller proportion of ‘non-risky’ households that were swapped. Every swapped record was matched with another record in another area at the record’s lowest non-unique geography (e.g. a record risky at OA but not at MSOA was swapped with another record outside the OA but within the MSOA); these were matched on household profiles that included basic demographic variables. At the very least, households were matched on household size so as to not affect total population size, except in the cases of large households (size 8+) where the sizes may have been slightly different. Some effort was made to match a risky record in one area with another risky record in another area.

Given the specific risk scenario outlined in the previous section, it is proposed that we only swap risky records, and we swap all records that are risky based on a much larger number of variables. We propose to swap all OA-risky records between different MSOAs to increase the uncertainty that a very near neighbouring OA could house a risky individual. Finding households with which to match could lead to non-risky households being swapped with those risky households. As in 2011, this means that every household has a chance of being swapped.

**7.2 Disclosure Checks (Business Rules)**

In making possible the construction of tables from an on-line table builder, it is important to note that not every combination of variables will be available for every level of geography. Indeed, if that were the case, we would effectively be providing individual level microdata where the perturbation could be unpicked from the billions of different combinations of variables and variable breakdowns. Albeit that the resultant microdata would be post-swapping, the perception would (correctly) be that we would be providing personal information for every census respondent, though some might not be quite in the right geographic area. Certainly, it would be straightforward to identify individuals from knowing a few of their details and roughly where they live, and thus discover the remainder of their information.

The disclosure checks are the rules by which decisions can be made as to whether to allow release of outputs pertaining to specific combinations of variables. In previous censuses, the policy has always been to assess whether the release of tables is acceptable for all areas, and so every table that was passed was available for every area. That did mean that tables that might have been acceptable for some areas were not released because the corresponding table was not acceptable for other areas. This was particularly the case for some tables with ethnic group or country of birth, where such minority populations might be clustered in a small number of metropolitan city areas. Our aim for 2021 is to make tables available for those areas where the disclosure risk would be sufficiently low, rather than reject for all areas because some would incur higher risk. We refer to the two approaches as the ‘*blanket*’ approach – where tables are produced for all areas, and the ‘*patchwork*’ approach – where tables are produced for the subset of areas where the risk is sufficiently low. Note that we can set parameters that define this risk, and so these disclosure checks can be applied within the online table builder, rather than manually, which is a major benefit and hence outputs can be published much faster this time.

We will still be making many oft-requested tables available on a blanket basis through the Table Builder, if available in previous censuses, due to the greater protection of swapping and the cell key method in 2021. The rationale is that if they were sufficiently protected in 2011, they will be at least as well protected in 2021. The patchwork approach mostly covers combinations of variables and categories that were not published in 2011 and provided subject to one or more rules. The parameters have not been set and we need to take into account uncertainty introduced by imputation and swapping. Work is ongoing on considering which rules are appropriate and the parameters within them.

**7.3 Perturbing Counts at high Geographies**

ONS SDC is aiming to apply cell perturbation as a protection against differencing, which is not automatically provided by record swapping. Since disclosure by differencing is a higher risk for lower geography tables, and unperturbed counts at higher geographies are desirable to users, ONS considered an option of leaving higher geography tables without perturbation. A possible issue with this is it allows comparison of some perturbed and known unperturbed values. If for example Local Authority District level tables were unchanged – and known to be so, an LAD table could be produced (with no perturbation) then compared with the sum of the MSOA counts (and some perturbations) within that LAD. In many cases it is not possible to unpick the perturbation and determine the level of perturbation but the exceptions to this are low counts, especially of 1, at the lowest level of geography at which perturbation is not carried out. Even then, there is almost always uncertainty as to the perturbation present within the cell counts of the lower geographies.

This method does introduce uncertainty when attempting to make comparisons between unperturbed counts at one geography and perturbed counts at a lower geography. However, the counts that are both low and *known* to be unperturbed are the issue, even if the geography is high.

The Census Table Builder for 2021 is planned to allow filtering outputs by population, e.g. to release counts for just household reference persons, by household type (communal establishment or household), and the residency status of the individual (long-term resident, student or short-term resident).

Though these filtered tables may pass the disclosure checks individually and be provided to the user (we call these T1, T2, which use the same variables but a different filter), the user would then be able to “difference” one table from the other by subtraction to obtain a table (T3= T1-T2) that could fail the disclosure checks and not otherwise be provided.

To assess the risk of differencing two such tables, several hundred tables were built on test census data for the East of England. These were built using different filters (T1, T2), and the difference between these filtered tables (T3). Differencing was not possible in the majority of attempted cases (98%) as one of the T1, T2, tables would fail the checks and not be available.

At MSOA level: of the tables that were available for both T1 and T2, approx. 40% of T3s would pass the checks and be available if requested. 60% of T3 tables obtained would have failed the checks. At LAD level the reverse was true: 60% of available T3 tables would pass, and 40% would have failed.

Given the deliberate design of variable output categories and based on the breakdowns currently available in the prototype table builder, differencing between two breakdowns of the same (non-geographic) variable was designed to be unlikely. The hierarchical structure of different breakdowns of the same variable was key here.

The risk of differencing using population filters was found to be lower at LAD than at MSOA but not significantly so. The differencing risk was comparable between MSOA and LAD, and so the evidence did not indicate that cell-key perturbation was unnecessary at LAD level. The conclusion therefore is that we should perturb all tables at all geographies.

**7.4 Transferability**

**7.4.1 Administrative Data and Integrated Outputs**

The use of data from administrative sources will be a feature in the outputs in 2021. The traditional census will also be supplemented by variables, from other sources, that will be linked/matched to the census microdata. Initially, the focus is on number of rooms (from Valuation Office Agency (VOA)) and income (from HMRC/DWP), but some more may emerge later. Where outputs include both those from the main questionnaire and those from other sources, these are referred to as integrated outputs.

The protection of these integrated outputs will again be the targeted record swapping followed by the cell key perturbation. There are two cases, one where the variable is available at the same time as the standard census variables, and one where the variable would become available later and subsequently added to the database / table builder already in place. In the former, the variable *might* be able to be used in the targeted swapping to protect unusual cases, but in the latter, there would be a need for a risk assessment for the level of detail and banding that would be appropriate.

In many cases, the linked source will have partial coverage within the enhanced dataset, and the data quality may be lower than in the census. Considering that, the disclosure risk should increase only negligibly with the additional variables. However, there could be a significant increase in risk if the external source data are wholly or partly in the public domain and can be linked or matched extremely well. If that were the case, it may be possible for an intruder to assign an identifier from the external source to a cell count of 1 that transpires from the table builder, and subsequently find out further information about this identified person by requesting other tables, perhaps one variable at a time. Alternatively, it may be possible at low geographies for an intruder to unpick parts of the record swapping by noting existence of an unusual combination of categories within the variables in the public domain. This may be addressed by applying coarser coding on these variables within the table builder so that it is not possible to identify the individual from them.

**7.4.2 Other Datasets**

More generally, there is great potential for the table builder to be employed for other data collections and outputs. However, it must be stressed once again that this is not a ‘plug and play’ method to protect data from any source. Its use for any datasets depends on the parameterisation specific to the data. Aspects that might influence the type and level of protection required include: data quality, sampling fraction, coverage, level of imputation, age of the data, sensitivity and risk appetite.

Though it is probable that a table builder could be used in some shape or form to satisfy the output needs, any other data source will require a fresh disclosure risk assessment. The disclosure control package for the traditional census is proposed as targeted record swapping as the primary protection method, supported by a secondary light touch cell key method, but work is required to assess the needs with e.g. data from administrative source(s), which may have differential quality. They may well require different protection methods due to different risk scenarios, and even if we were to use record swapping and the cell key method, the parameterisation will need a separate assessment. It is likely that the parameters will often be quite different to those used for the traditional census and establishing these will require significant input from the ONS SDC team. Moreover, one must ensure that the protection cannot be unpicked by comparison of integrated outputs with those from the admin source, since each will contain the similar ‘admin data’ variables. How much the cell key method can protect against this comparison is unclear, and furthermore it is unlikely that the swapping can be carried out on the same records in the two sources.

1. **Harmonisation**

ONS, NRS and NISRA are broadly harmonised on the use of targeted record swapping and the cell key method. However, there will be differences between the countries on some of the specific details within the approach. Known and likely variations are:-

* The variables used to assess risk prior to the swapping procedures are likely to differ slightly (to take account of the different questions asked and population differences), as are the variables and profiles for matching to find a household with which to swap.
* When the record swapping is run, it is likely that new ‘uniques’ will be created – records that are still in their true output area (they may originally have been one of two or three with a specific value in variable A, and the others may have been swapped based on uniqueness in other variables). ONS is considering whether to run a second round of swapping targeting these. Current investigation of the uniques swapping code would indicate that due to the high swapping rate it is unlikely that NRS will do an extra round of this, and are planning to run targeted record swapping similar to that run in 2011.
* The three Offices will each set their own perturbation rate within the cell key method (though they *may* be harmonised or similar). It is likely that the specific rates for perturbing 1s and 2s will differ.
* ONS and NRS aim to apply the methods within the flexible table builder, while NISRA’s intention is to apply the methods to pre-defined data cubes, which may reduce the number of variable combinations possible.
* The geographic level above which all tables would be provided unperturbed is still under investigation. UKCC were comfortable with all tables at *all geographies* being perturbed, but this is the subject of further work to assess differencing risk (and impact) at high geographies (see Section 7.3). It is possible that different countries will make different decisions here.
* There has been no agreement or decision yet as to whether to perturb totals separately or to make the totals the sum of the perturbed cells. All the figures would be available so the issue is mainly presentational but the ONS preference currently is to present each individual table as internally additive.
* The disclosure checks (business rules) in the table builder will almost certainly differ. This aspect is still very much under investigation. ONS is likely to have some pre-defined queries available for all areas but most queries will be subject to the ‘patchwork’ approach, where the output will only be available for areas that pass the business rules. NRS is likely to use rules based around sparsity, number of variables and limit specific combinations, and be based on the ‘blanket’ approach.

**9. Other Census products**

This paper has so far not covered any products outside the frequency tables for combinations of the standard and derived census variables. However, we are aware that there will be different strategies for several other products for 2021 UK Census for which there is a user need.

**9.1 Microdata samples**

These are now an established output from the decennial census, with 1991, 2001 and 2011 samples produced at the time, as well as the samples derived from 1961, 1971 and 1981 Censuses as part of the Enhancing and Enriching Historic Census Microdata (EEHCM) project <https://www.ukdataservice.ac.uk/about-us/our-rd/historic-census-microdata> now held at UK Data Service. There is an established Census Microdata Working Group – with external representation – that monitors and discusses progress. The general feeling is to have similar products to those of 2011 and, given the general satisfaction of users, to employ similar disclosure techniques. The level of disclosure risk will vary from negligible (for the public ‘teaching’ dataset) to different balances of risk/utility based on access and licensing conditions.

In 2011 UK Census, the suite of microdata products was:

* 1% public use (teaching dataset) of individuals, regional geography
* 5% safeguarded sample of individuals, regional geography
* 5% safeguarded sample of individuals, grouped local authorities
* 10% secure sample of individuals, local authority geography
* 10% secure sample of households, local authority geography

One aim for 2021 Census is to produce a safeguarded (end user licence, EUL) household microdata sample. This has proved challenging in previous censuses due to real and perceived disclosure risk, along with the difficulty in enforcing meaningful sanctions in the case if there were to be a user breach. However, for many years ONS has produced safeguarded/EUL microdata for sample surveys and there are established GSS disclosure guidelines for these (ONS, 2014).

The disclosure risk for sample survey microdata is theoretically greater than for *samples* of census data. The sampling for the survey microdata is prior to response so any survey respondent would know that they would be included in the microdata. The sampling for census microdata would be subsequent to response so, though I would know my response is included in the census database, I would not know whether I am included in the census sample microdata. This is an important point in assessing the risk of someone being identified within the microdata sample. With survey microdata, if I know someone who responded to the survey, a potential identification is more likely to be correct, especially if they are unique in the sample on a set of attributes that I think I know about them. In the census case, I may only be looking at a relatively small sample (10% or less) so there is some uncertainty that a potential identification is correct.

All the sample proportions are kept low to maintain this uncertainty and the intention is for the safeguarded household file to be between 1% and 3% of households. The precise specification of variables and categories is in the agreement/development stage but will follow the spirit of the GSS survey microdata guidelines (ONS, 2014).

**9.2 Origin-destination tables**

Since 2001, ONS have released tables based on combinations of two geographies. These can be extremely geographically detailed and very sparsely populated. Many consist chiefly of cell counts of zero and sporadic cell counts of one. In those cases, the tables mimic a scattering of individuals.

In 2011, there were four categories of origin-destination tables:

* Area of residence by area of workplace (SWS)
* Area of residence by area of residence one year ago (SMS)
* Area of residence by area of student term-time address (SSS)
* Area of residence by area of second address (SAS)

The sparsity of these tables can be seen by considering the total population in combination with the number of geographies. Figures from 2011 Census indicate, for those categories within England and Wales:

SWS: 26.53 million population (those in employment)

SMS: 6.84 million (those changing address in year prior to the census)

SSS: 0.69 million (students)

SAS: 2.90 million (those with a second address, somewhere where they live at least 30 days in the previous 12 months)

LAD to LAD: 348 \* 348 = 121,104 possible flows

MSOA to MSOA: 7,201 \* 7,201 ≈ 51.8 million

OA to OA: 181,408 \* 181,408 ≈ 33 billion.

Those flow counts are the number of possible distinct flows, even before any breakdown by age, sex, mode of travel to work, economic activity or any other variable. In the case of OA to OA tables where the flow is within England and Wales, there would less than 1 person travelling to work (including those that work at home) for every thousand cells. Naturally, some of the flows are extremely unlikely due to distance, but it is the unusual (long distance) yet real flows where the protection is more likely to be needed, especially where there is any additional breakdown.

These are extremely difficult to protect using only traditional disclosure control methods. Record swapping applies some protection, but the level of swapping required to apply sufficient protection for all the products required would be prohibitive to any sense of data quality. In 2001, the small cell adjustment method was employed, with all tables being made freely available, but resulted in very poor utility for most users using low level geographies. In 2011, with no post-tabular adjustment, the tables were separated into those available publicly, under safeguarded licence and in a secure setting. The tables thus had high utility but access was often more difficult. The approach for 2021 must address both utility and access, while still protecting confidentiality. There is an established Census Origin-Destination Working Group – with external representation – that monitors and discusses progress.

The current thinking is to use a ‘patchwork’ approach to supply breakdowns for those flows in areas that achieve defined thresholds. ONS SDC presented this approach at the Privacy in Statistical Databases conference in Valencia in September 2018 (Dove et al., 2018). While all flows (with no breakdowns) should be available publicly, the main disclosure risk comes from breaking those down further, especially when the flow is small.

Table 4. Exemplar OA to OA Residence to Workplace Flow Table

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Area of Workplace | | | | | | |
|  |  | OA1 | OA2 | OA3 | OA4 | OA5 | OA6 | OA7 |
| Area of Residence | OA1 | 12 | 5 | 0 | 2 | 6 | 0 | 1 |
| OA2 | 3 | 23 | 0 | 5 | 2 | 7 | 3 |
| OA3 | 1 | 8 | 2 | 5 | 1 | 0 | 3 |
| OA4 | 0 | 4 | 0 | 19 | 1 | 2 | 1 |
| OA5 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| OA6 | 2 | 2 | 1 | 7 | 0 | 6 | 1 |
| OA7 | 2 | 3 | 1 | 1 | 2 | 0 | 8 |

Table 4 shows a section of an origin-destination table with the numbers of people travelling from their area of residence to area of workplace. We should not be overly concerned about small counts here[[4]](#footnote-4). For instance, the one person who travels from residence in OA1 to workplace in OA7 cannot be identified except through private information, in fact, only by already knowing all the information pertaining to the person in that cell. I may know someone who lives in OA1; I may know someone who works in OA7; but neither piece of information is enough to place them in the OA1 to OA7 cell. If I can place them, I must know all the information anyway and so I am not finding out anything new about that individual. You may notice that the one person who lives in OA5 commutes to OA4, so is an apparent disclosure but since this is a localised cut of a much larger matrix and there will (or at least *could*) be others who commute from OA5 to other OAs not in this subsection of the table.

If we now consider just the first row of the table (Table 4), and provide additional detail on, say, health (see Table 5), we see that the flows are broken down into five categories. Let’s assume, not unrealistically, we know one’s area of residence and workplace but do not know their health status. We can discover:

* The one OA1 to OA7 commuter has Fair Health
* All the OA1 to OA5 commuters have Good Health

The first is a clear attribute disclosure and I discover something about a person that I didn’t previously know. We should certainly protect against this. Even though there will be some protection through record swapping, the level of swapping is kept reasonably low so as not to destroy the utility of the data. Moreover, the flow itself is not the issue; it is the additional attribution of health to that individual. In the context of many origin-destination tables being available, the biggest risk is that an intruder would be able to build up a more detailed record for that one person, from tables of OA to OA by age, OA to OA by economic activity, etc.

The second is a group attribute disclosure and is more interesting. If I know someone (one of the six) who commutes from OA1 to OA5, I discover they have Good Health. There is still some doubt due to record swapping, but it is a disclosure of an attribute for those six. We are probably less concerned than for the first case, since the number is sufficiently high to be considered ‘the norm’. Furthermore, it is unlikely that different breakdowns for OA to OA would allow individual records to be built up due to the unlikelihood of there being a series of other group attribute disclosures for that OA1 to OA5 flow of 6 individuals.

The approach that we are proposing to take is to apply a threshold for the breakdowns. While the flow itself will be published, the threshold for the breakdown should normally be 5 persons. The proposed final table for release is shown in Table 6. This now allows breakdowns for the major flows to be published where, in previous censuses, it is likely that none of those would be available publicly.

Table 5. Exemplar OA to OA Residence to Workplace Table, broken down by Health.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Residence | Workplace | Flow | Very Good Health | Good Health | Fair Health | Poor Health | Very Poor Health |
| OA1 | OA1 | **12** | 8 | 2 | 0 | 2 | 0 |
| OA1 | OA2 | **5** | 1 | 1 | 3 | 0 | 0 |
| OA1 | OA3 | **0** | 0 | 0 | 0 | 0 | 0 |
| OA1 | OA4 | **2** | 1 | 0 | 0 | 1 | 0 |
| OA1 | OA5 | **6** | 6 | 0 | 0 | 0 | 0 |
| OA1 | OA6 | **0** | 0 | 0 | 0 | 0 | 0 |
| OA1 | OA7 | **1** | 0 | 0 | 1 | 0 | 0 |

Table 6. Exemplar OA to OA Residence to Workplace Table, broken down by Health (proposed release).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Residence | Workplace | Flow | Very Good Health | Good Health | Fair Health | Poor Health | Very Poor Health |
| OA1 | OA1 | **12** | 8 | 2 | 0 | 2 | 0 |
| OA1 | OA2 | **5** | 1 | 1 | 3 | 0 | 0 |
| OA1 | OA3 | **0** | - | - | - | - | - |
| OA1 | OA4 | **2** | - | - | - | - | - |
| OA1 | OA5 | **6** | 6 | 0 | 0 | 0 | 0 |
| OA1 | OA6 | **0** | - | - | - | - | - |
| OA1 | OA7 | **1** | - | - | - | - | - |

We are also proposing that asymmetric tables are also made available, e.g. OA to MSOA, or LAD to OA. Some of these have been made available via the commissioned tables service (see 9.5) for specific local areas in previous censuses. The key risk to assess here is that of disclosure by differencing, which may be addressed by using the cell key method.

**9.3 Non-standard Geographies**

These are tables for ‘difficult geographies’ that are not suitable for the standard ‘best fit’ approach. The GSS Geography Policy is for all outputs to be ‘best fit’ to output area geography (ONS, 2015). This addresses the risk of creating geographic slivers between bespoke and standard geographies. However, there are exceptions where the best fit approach is less suitable. The two most apparent are **National Parks**, where there are instances of large differences between populations relating to the ‘exact’ boundaries and the ‘best fit’ geography; and **parishes**, where many are smaller than output areas (and where the desired volume of outputs is small). The solution to the former is straightforward, as in 2011, where exact fit counts and a small number of breakdowns were supplied for National Parks. Discussions continue between Census, ONS Geography and ONS SDC on the best solution for parishes.

One of the successes of 2011 was the advent of **workplace zones** to help provide a more appropriate geography for workplace statistics, where ONS SDC worked closely with ONS Geography and University of Southampton to address disclosure risk. Very few workplace tables were released at low geographies in 2001 since even moderately sized workplaces could dominate output areas in non-urban areas, while some urban output areas could have massive workplace populations. So a new workplace geography was created as output areas with small workplace populations were grouped together, while those output areas with large workplace populations could be split. This allowed more to be provided publicly in all areas across the country, and this particularly benefited some of the origin-destination outputs. For 2021, it is a working assumption that workplace zones will be updated to reflect rises, falls and movements in the workplace populations in these areas.

The anticipation is that ONS will follow the Eurostat requirement for a population count and some univariate outputs for 1 km **grid squares**. For sparsely populated areas where a 1 km square may only have a small population, there may be some shifting of population so that all squares are over threshold. Census and ONS Geography are considering whether to provide information for smaller grids where population is most concentrated, and are likely to provide for 500, 250 or 125 metre squares where the population is sufficient.

**9.4 Small populations**

These are special sets of tables produced for populations that are neither available in standard tables nor in the Flexible Table Builder. These are predominantly for individuals from ethnic groups, religions and countries of birth in the write-in categories which may have small numbers overall but are clustered geographically around England and Wales. Examples from 2011 Census were Kashmiri, Ravadashian, Albanian COB, Kuwait COB. Analogous to the patchwork approach, the breakdowns are only released for areas that have population above given thresholds: e.g. MSOA100, MSOA200 and LAD100.

**9.5 Commissioned tables service**

The Table Builder will not accommodate all the possible tables from the census database. Where the request is rather esoteric, there will still be a significant need for a service to produce bespoke or commissioned tables. It is imagined that the need might not be as great initially as for previous censuses, though making greater numbers of tables available for more areas may stimulate greater interest in census products. The SDC team will need to produce advice and guidance for those bespoke tables.

Some examples of tables commissioned from the 2001 and 2011 Censuses that would be challenging to reproduce in a Table Builder are:

**Non-standard aggregation of variables/cross tabulation:**

1. Household type (selected categories) by number of dependent children in household aged 0 to 15 years old by hours worked of parents (workers in generation 1 in family)
2. Sex and country of birth of parent(s) by sex (of dependent children) by sex of oldest sibling(s)
3. Academic cohort of birth (1945/46 to 1969/70) by qualifications gained by sex by marital and civil partnership status

**Distinct populations**

1. All usual residents aged 18 or over qualified to vote in the UK parliamentary elections
2. All households where no member has Jewish religion but at least one has Jewish ethnic group (write-in response)
3. All usual residents aged 16 to 50 in households where the HRP is aged 65 or over

**Bespoke geographies:**

1. Postal sectors in England and Wales
2. IMD2004 deciles based on 2011 LSOAs in England
3. Origin Destination: Origin: Area of residence one year before the Census: Primary Urban Areas in England and Wales; Remainder of each region in England and Wales; Northern Ireland; Scotland; Outside the UK

Destination: Area of residence on Census day (27 March 2011): Primary Urban Areas in England and Wales; Remainder of England and Wales

All of these would be purpose built by a team in ONS Census and be subject to the same cell key perturbation as those tables passing through the Table Builder. The same disclosure checks (business rules) would apply but there would be scope for ‘manual’ risk assessment if necessary.

1. **Assurance and Challenge**

The ONS Census Research Assurance Group (CRAG) has overseen progress on this work and questions and issues raised have been addressed, while the direction has been approved. The External Assurance Panel (October 2018 and October 2019) were happy with the direction and supported later by the UK Census Committee in November 2018. As the work progressed, we have had regular discussions and input from the UK Outputs and Dissemination Harmonised Working Group. The work, at different stages, has been presented at UNECE Conference 2017 (Spicer, 2017) and Privacy in Statistical Databases Conference 2018 (Dove et al, 2018). The broad methods were adopted by Eurostat as the default for the 28 current EU nations to provide tables and hypercubes to Eurostat in the 2020/1 Census round.

There has been user engagement as part of Census Outputs consultation, and for which there was general support for the SDC approach, and with the Microdata Working Group and Origin-Destination Working Group, both of which have external academic, public and private sector representation.

As part of the assurance, Martin Serpell (University of West of England, UWE) was provided with a small number of tables with variables in common, with the cell key perturbation method, on synthetic data generated to mimic census data. While the overlapping of these tables and UWE Un-picker tool together reduced the amount of uncertainty in cell counts in these tables, with a further rebalancing tool he was able to create estimates that of which 92-99% are within +/-2 of the true cell values. In follow-up correspondence, he estimated that he could estimate around 40% of small counts correctly.

The main concern for ONS is the prospect of unpicking with certainty or high confidence. If an intruder ultimately has uncertainty in their estimates of ±2, then the cell-key method had still introduced uncertainty into the cell values. Record swapping is the main source of protection, and cell-key perturbation is intended mainly to protect against differencing.

Further work was agreed:

* ONS SDC should work with Martin to assess risk and create a test bed for using his unpicker and rebalancing tools. The unpicker tool and rebalancing algorithm are simple to run with different inputs, and we should work to create the software capability within ONS.
* ONS should form success criteria which would outline an acceptable level of risk or unpicking. The data will never be zero risk; there is always a small risk with released data, but the question is how much is acceptable. The parameterisation of these methods has not been fixed and ONS SDC should continue to test different perturbation tables and distributions to assess the effect on level of risk (and utility).
* Communications will also need to be developed to educate users about this approach – communications are a large part of census research, and that is underway.

We are committing to running an intruder testing exercise on the Table Builder outputs constructible from 2021 Census data. A similar exercise was undertaken on 2011 Census tables prior to release (see Spicer et al, 2013). This is not quite the same as a reconstruction attack. The bar is not just to establish that a cell count is a true 1 but to identify an individual, that is, put a name to a number, possibly attributing new information to that individual. One of the emphases will be on the use of social media. Since the 2011 Census exercise it is clear that a key strategy for intruders – or at least intruder testers – is to match or link datasets to information on social media. Indeed, the ONS (2017) review of ONS special licence datasets showed that the risks were very high for some specific groups, such as the self-employed or those born outside UK, especially at lower geographies.

The expansion of social media platforms and ‘mass self-disclosure’ pose real challenges. A good chapter on this area appears in Masur (2019). Privacy settings do not always keep information private, since comments, likes, shares and re-tweets may reach a wider audience than originally intended. A paradox exists where an individual may happily and wilfully expose very detailed intimate details about themselves on social media but be outraged if it were perceived that similar or less detail could be derived from statistics released by an official body (such as the ONS). It is therefore extremely difficult to draw the line between what should be considered public and what is private. If ONS data did expose something that is already in the public domain then ONS would not be breaching the SRSA but the perception of the individual may well be that care was not being taken of their census return.

The intruder testing for 2021 will take the form of the table builder being presented, prior to wider release, to expert users, recruited from both within and outside ONS. These “friendly intruders” will be given a limited amount of time to attempt to identify individuals and disclose information about them, using any tables that can be constructed, along with any information from unlimited internet access. This exercise will all take place within a safe setting and all claims will be assessed by ONS staff. Of course, the security and confidentiality of the census data will be paramount during this exercise.

1. **Summary**

This paper has set out the need for disclosure control, put into context alongside the history of data protection in previous censuses. To help focus priorities on outputs and the disclosure control methodology for 2021 Census, development work has considered a strategy which targets user concern in the three areas of outputs highlighted by UK Statistics Authority after 2011:

a. Accessibility – Users reported difficulty in locating specific items, in part compounded by the dissemination approach of publishing a high number of predefined tables.

b. Flexibility – Users reported a desire to create their own outputs and frustration with decisions taken on the level of detail made available.

c. Timeliness – Users expressed disappointment that no substantial improvement had been made in 2011 compared to the release of 2001 Census outputs.

Timeliness and flexibility can be addressed through the availability of an on-line table builder, allowing a user to define the table that they require. The level of detail that a user can be allowed is subject to the assessment of disclosure risk that that combination of variables and geography will generate. UK Census Committee (UKCC) has agreed that the favoured option to be researched was a combination of pre-tabular targeted record swapping and a post-tabular cell perturbation (cell key) method. While record swapping is the main protection for outputs in 2021, the cell key method offers additional considerable protection against disclosure by differencing and thus allows the desire for user defined on-line tables to be realised.

Alongside targeted record swapping, that was used in 2011 and is being enhanced, the basis of the post-tabular methodology had been previously developed by Australian Bureau of Statistics (ABS), with enhancements developed by ONS SDC Methodology to make this suitable for use in the 2021 UK Census. In particular, the provision of low counts must be supported by an algorithm to perturb zeros, which protects against ‘disclosure of existence’. The weaknesses of the previous census, including flexibility and timeliness, are addressed head on by such a system, though balanced by a small amount of inconsistencies between different tables. This approach has been shared with the Eurostat SDC Expert Working Group and adopted as the recommended approach for the 28 EU NSIs for protecting hypercubes from the 2020/2021 Census round (Giessing and Schulte Nordholt, 2017).

Further work is indeed necessary to refine the parameterisation of all aspects of the methods, especially in the light of the UWE challenge and the general direction of the US Census Bureau and others towards differential privacy. Whilst further developing our thinking and methodology, Census Outputs and SDC have been engaging further with users to assess their appetite for our approach, and to maximise the amount of information that can be gleaned from such a table builder. Work is currently taking place on the disclosure checks that are required to decide which combinations of variables, categories and geographies will be permitted. The preferred approach for 2021 is to allow each output to be provided for those areas for which the data are sufficiently low risk (a 'patchwork' approach), as opposed to a blanket 'everywhere or nowhere' policy employed in previous censuses (an example here is a table using detailed ethnic group that might be available in some areas in cities with greater ethnic diversity). This should facilitate greater amounts of information to be disseminated where previously blocked.

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**Relevant Legislation**

Data Protection Act (2018) <http://www.legislation.gov.uk/ukpga/2018/12/section/35>

General Data Protection Regulation (in force in UK May 2018): Overview. <https://ico.org.uk/for-organisations/data-protection-reform/overview-of-the-gdpr/>

Statistics and Registration Service Act (2007) <http://www.legislation.gov.uk/ukpga/2007/18/section/39>

UK Statistics Authority Code of Practice for Official Statistics (2009) <https://www.statisticsauthority.gov.uk/wp-content/uploads/2015/12/images-codeofpracticeforofficialstatisticsjanuary2009_tcm97-25306.pdf>

1. Note that US Census Bureau are considering an alternative approach for 2020 Census, consistent with the differential privacy paradigm. This is along the lines of adding noise to cell counts in tables. [↑](#footnote-ref-1)
2. Records that have been either imputed or swapped are given a record key of 0. In that way, cells that comprise entirely of imputed or swapped records can be controlled to be not perturbed. [↑](#footnote-ref-2)
3. The cell keys are not assigned zero in case a table is produced with all cells with zero counts happening to be structural. This does therefore not preclude entirely the chance of a structural zero being perturbed. [↑](#footnote-ref-3)
4. There are a couple of exceptions to this. If I know either area of residence or area of workplace and I have partial information on the other, I may be able to pinpoint them with more precision. For example, if I know my next-door neighbour commutes a long way (to a named town), it may be that there is only one person who commutes from my (their) home OA to any OA in that town. Hence, I could discover their OA of workplace. The logic is similar for the converse where I may know that a work colleague has a long commute from a named town. Note that both the record swapping and the cell key perturbation will offer some protection against this sort of ‘partial disclosure’ which relies on private knowledge [↑](#footnote-ref-4)