# The U.S. Census Bureau's Ex Post Confidentiality Analysis of the 2010 Census Data Publications

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**Abstract:** We reconstruct 2010 Census person records from 34 published tables. Using binned age, only 10% of reconstructed records differ from their confidential source on even a single bit. With only published data, an attacker can verify perfect reconstruction accuracy for 70% of all census blocks (97 million people). These detailed tabular summaries have similar risk of prohibited disclosures as the unreleased confidential microdata. Reidentification studies confirm that an attacker can, within blocks with perfect reconstruction accuracy, achieve over 90% precision for population uniques with nonmodal characteristics, far greater precision than statistical models. The fatal flaw in the methods used for the 2010 Census is that they do not compose. The framework used for 2020 Census publications, which does compose, defends against this attack.

**One-Sentence Summary:** The method used to prevent disclosure of confidential information in the 2010 Census failed and could not be used for the 2020 Census.

Data products from the United States Decennial Census of Population and Housing are widely used for policy, research, and community planning including the allocation of approximately $1.5 trillion to state and local governments, nonprofits, businesses, and households *(1)*. Tens of billions of statistics are published, almost all at the most granular level of geographic detail—the census block. Publishing so many statistics in such fine detail raises a critical question that has troubled the agency for decades: can those statistics be used to accurately pinpoint specific individuals in the published data? If so, is this reconstructed image a threat to reidentification of the individual's census responses? For the 1990, 2000 and 2010 Censuses, aggregation, age coarsening, noise infusion via targeted geographic identifier swapping, and, in 2010, partially synthetic data were used as the statistical disclosure limitation (SDL) framework to protect confidentiality *(2)*. We study the extent to which these SDL procedures limited the accuracy of reconstructed microdata and impeded reidentification.

We reconstruct the underlying person-level records (called microdata) for the features of census *block*, *sex*, *age*, *race*, and *ethnicity* using only publicly released tables.[i] We then match the reconstructed records to records in a commercial database acquired during the conduct of the 2010 Census containing personal identifiers and to a high-quality personal identifier database constructed from an extract of the 2010 Census data themselves. Our unique contributions to this literature are:

- first statistical agency demonstration that reconstruction predicted by *(3)* is feasible at scale using its flagship publication;
- complete empirical demonstration that using separate, incompatible, confidentiality protection frameworks for tabular and microdata publications fails if the tabular data are too detailed;
- first mathematical proof requiring no confidential data that a large, identifiable subset of reconstructed records are the exact image of the underlying confidential records for the stated feature set;
- first mathematical proof of an upper bound on the percentage of reconstructed records that can differ on no more than a single bit from their confidential image on the stated feature set;
- empirical demonstration that neither aggregation nor collapsing age into narrow bins prevents high-precision reidentification of census respondents;
- first empirical demonstration that reconstructed microdata succeed in reidentifying vulnerable individuals with precision rates much higher than statistical baselines—racial and ethnic minorities in this work, but they could be other sensitive characteristics like occupancy-code violations or same sex partners using other 2010 Census publications;
- placing the entire reconstruction workflow in the public domain, permitting others to assess the risk in the many similar products published by statistical agencies and private information suppliers;
- definitive demonstration that the differential privacy framework used for the 2020 Census in its May 25, 2023 release defends against this attack at the parameter values used to produce the 2020 Census Demographic and Housing Characteristics File—successor to the 2010 Census Summary File 1.

The 2020 Census Disclosure Avoidance System (DAS) took six years to develop, and the portion that produces the data comparable to those studied in this paper was finalized in

November 2022. The decision in 2018 to use a differentially private framework for the DAS was based exclusively on the reconstruction results; however, continuous research confirmed that reconstruction risk does imply privacy-violating reidentification risk Our contributions are timely because traditional disclosure limitation experts continue to dispute the efficacy of reconstruction-based attacks *(4, 5)* using incomplete formulations of the problem, and domain experts continue to assert that the methods are no better than guessing *(6,7)* or ineffective *(8)*. Consequently, the analysis of how to properly assess the disclosure risk associated with publishing massive tabulations from a single confidential input continues to focus on methods with the same flaws that our experimental attack exploits *(9)*. Every major textbook or review article on SDL *(10,11,12,13)* recommends using distinct methods for tabular and microdata that violate the mathematical property of composition[ii]—precisely the flaw that our attack exploits and the recommendation that our research challenges. If these practices remain in widespread use by statistical agencies and other data publishers, the vulnerability we exposed remains a known, undefended risk in these publications.

To frame our results, our analyses focus on small populations with uncommon characteristics—persons living in a single census block. We isolate inferences that are only possible because a person participated in the 2010 Census—because the actual census response for that individual was used—from inferences that depend on properties of the small population itself. Borrowing a key insight from differential privacy *(14)*, we argue that inferences depending critically on the presence of one person's data are the natural province of SDL frameworks because they are potential confidentiality breaches whereas those depending on properties of the small population are generalizable scientific inferences. We call this approach leave-one-out (LOO) reasoning. See also the supplementary text on distinguishing privacy breaches from generalizable inferences.

We do not employ all aspects of the differential privacy framework, however. We do not consider all possible attacks—where it would be easy to prove that the privacy loss for SDL implemented via geographic identifier swapping is infinite. Instead, we take the core intuition—confidentiality cannot be breached if a person's data are not included in the records used for tabulation—and apply it directly to the analysis of our reconstruction-abetted reidentification attack. Thus, our attack model is optimistic not worst-case. Accurate scientific inference about a particular person can still be harmful even if it does not require their response to attain high precision. This is an important policy consideration for statistical agencies but not a confidentiality issue.

## The Importance of Confidentiality for the Census

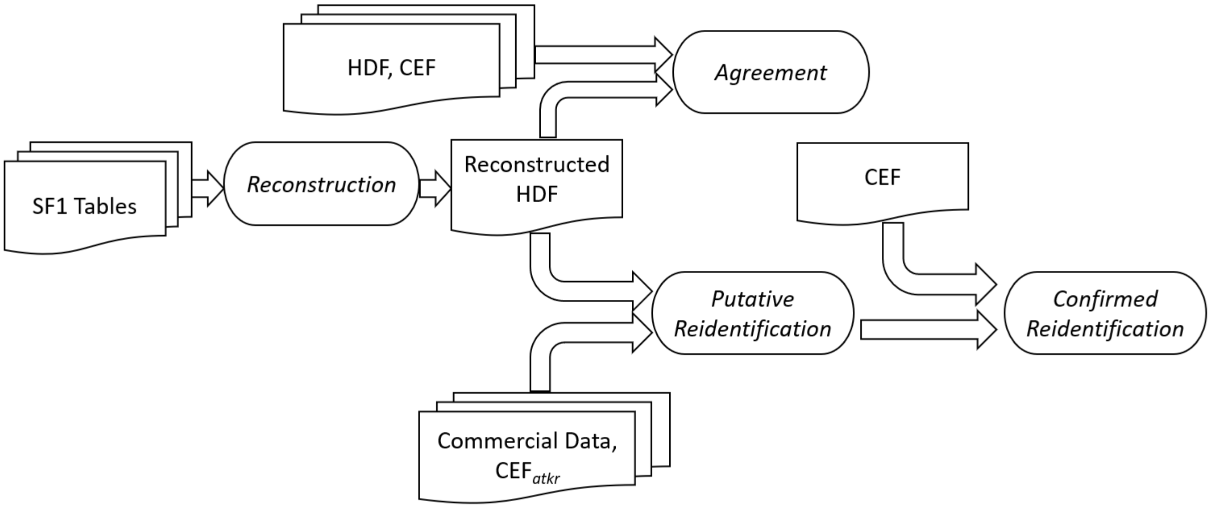
Title 13 of the U.S. Code mandates that information gathered from individuals and establishments remain confidential. Sections 8(b) and 9 prohibit releasing "any publication whereby the data furnished by any particular establishment or individual under this title can be identified." Additionally, since most information is collected by respondent reports, data quality requires public trust in the Census Bureau's protections so that truthful responses are given, especially to sensitive questions *(15, 16)*. Although written in 1954, before modern approaches to disclosure limitation were invented, and not mathematically explicit, Title 13's emphasis on data specifically furnished by respondent establishments or individuals is consistent with focusing analyses on inferences specifically enabled by the inclusion of an individual's respone in the 2010 Census. See the further discussion of confidentiality protection in the supplementary text, which includes the legal authorities and confidentiality protections constraining the U.S. Census Bureau.

## Related Work

Fellegi *(17)* introduced the problem of database reconstruction, that a confidential datum could be recovered by subtracting across related tables unless cells were systematically suppressed. This is the oldest known vulnerability that SDL addresses. Denning and Schlörer *(18)* coined the term “tracker” for an attacker who monitors the output of a statistical database looking for violations of confidentiality. The only way to protect a statistical database against subtraction or tracker attacks is to audit every proposed query before data release to understand its impact on the privacy properties and guarantees of all previous data releases. In 1995, Cox *(19)* proposed a query-auditing network integer program that, when a solution exists, provably defends a sequence of tabular releases from all subtraction attacks. In 2000, Kleinberg et al. *(20)* proved that query auditing is NP-hard.[iii] In 2003, Dinur and Nissim *(3)* demonstrated conditions under which a database could be efficiently reconstructed even when only perturbed queries were reported. Homer et al. *(21)* showed the failure of aggregation for genomic data. Dwork et al. *(22)* provide an overview of reidentification and reconstruction attacks. Older decennial census data have been used as part of a successful reidentification attack *(23)*. Recently *(31)* used nonconvex optimization methods to reconstruct microdata from census tabulations. They confirm the vulnerability found in our work *(32)*.[iv] See the supplementary text for additional reconstruction studies and their relationship to differential privacy.

## Methods

**Fig. 1.**


HDF, CEF
Agreement
SF1 Tables
Reconstruction
Reconstructed HDF
CEF
Putative Reidentification
Confirmed Reidentification
Commercial Data, CEF$_{atkr}$

**Overview of the reconstruction, agreement, and reidentification workflow.** Based on Summary File 1 (SF1) tables, a database with the features and rows of the confidential Hundred-percent Detail File (HDF) is reconstructed, validated for agreement with the HDF and the confidential Census Edited File (CEF), linked to commercial databases and an identifier-only copy of the CEF (labeled CEF$_{atkr}$) to determine putative reidentifications, then reidentifications are confirmed by linkage to the full-feature CEF.

Fig. 1 provides a schematic overview of the research design, the components of which are elaborated below. See also Fig. S1, Tables S1, S2, S3, and the Materials section of the supplementary text.

### *Data Used for the Experiments*

The 2010 Census Edited File (CEF) constitutes the final, fully edited, permanent electronic record of the responses to the 2010 Census. The application of SDL procedures, primarily household swapping of geographic identifiers, partial synthesis of group quarters responses, and coarsening of birth date to age applied to the CEF produces the Hundred-percent Detail File (HDF).[v] While the feature sets for the full hierarchical CEF and HDF data structures are much larger, the relevant feature sets for our experiments are derived from an antecedent file called the Census Unedited File (CUF) and the production editing.

As part of internal confidentiality safeguards, the *name* and *address* features are stored on the CUF, not the CEF. In the census processing, *address* is linked to an address identifier called the Master Address File Identifier (MAFID) that the Census Bureau's Geography Division has determined to be a living quarter that existed on April 1, 2010, as either a housing unit or an occupied group quarters facility, and thus in-scope for data collection in the 2010 Census. To facilitate research while safeguarding the *name* and *address* features, the Census Bureau creates a crosswalk that relates the internal person-record identifier on the CEF to a person identifier called a Protected Identification Key (PIK) using the production household data record-linkage system called the Person Identification Validation System (PVS).[vi] The MAFID was geocoded to the 2010 Census tabulation geography census block. The resulting feature sets for the portions of the CUF, CEF and HDF that we use are shown in Table 1.

**Table 1.**

| Dataset | *name* | *address* | *pik* | *block* | *sex* | *age* | *agebin* | *race* | *ethnicity* |
|---|---|---|---|---|---|---|---|---|---|
| CUF | x | x |  |  | x | x | y | x | x |
| CEF |  |  | x | x | x | x | y | x | x |
| HDF |  |  |  | x | x | z | y | x | x |
| COMRCL |  |  | x | x | x | x | y |  |  |
| CEF$_{atkr}$ |  |  | x | x | x | x | y |  |  |
| rHDF$_{b,t}$ |  |  |  | x | x | z | y | x | x |
| rHDF$_{b}$ |  |  |  | x | x |  | x | x | x |
| Putative rHDF$_{b,t}$ |  |  | x | x | x | z | y | x | x |
| Putative rHDF$_{b}$ |  |  | x | x | x |  | x | x | x |
| Confirmed rHDF$_{b,t}$ |  |  | x | x | x | z | y | x | x |
| Confirmed rHDF$_{b}$ |  |  | x | x | x |  | x | x | x |
| MDG |  |  | x | x | x | z | y | g | g |
| PRG |  |  | x | x | x | z | y | h | h |
| MDF |  |  |  | x | x | z | y | x | x |
| rMDF$_{b,t}$ |  |  |  | x | x | z | y | x | x |

Notes: The symbol x means the feature is present in the dataset. In all cases *age* is based on available birth date information and calculated as of April 1, 2010. The symbol y, used for the feature *agebin*, means the available age information is sufficient to recode to the binned age schema. The symbol z means that the *age* feature in this dataset aggregates ages 100–104, 105–109, and 110 or older into three bins. The rows beginning Putative and Confirmed refer to the output of reidentification experiments. The schemas for MDG and PRG include the variables required to select only putative reidentifications based on either rHDF$_{b,t}$ or rHDF$_{b}$. The symbol g means guess the mode of the block-level *race* × *ethnicity* table. The symbol h means guess *race* and *ethnicity* with probability proportional to the counts in the block-level *race* × *ethnicity* table. The rows labeled MDF and rMDF$_{b,t}$ refer to the output of the 2020 Census Disclosure Avoidance System TopDown Algorithm applied to the 2010 CEF. Throughout the text, features shown in this table are denoted in italics to distinguish them from ordinary uses of the same word.

Feature sets for all data files used in the reconstruction and reidentification experiments.

The other features shown in Table 1 are defined as follows: *block* is the 15-character census block identifier; *sex* is coded male or female; *age* is coded in single years from 0 to 109 with a top-coded category representing ages 110 or older (111 categories); *race* is coded as any combination of African American/Black, American Indian/Alaska Native, Asian, Native Hawaiian/Pacific Islander, White/Caucasian, or some other race except none of the above (63 categories); and *ethnicity* is coded Hispanic/Latino or not Hispanic/Latino. In the algorithms used to perform our experiments, we denote the feature sets shown in the rows of Table 1 as $P_{\text{Dataset}}$.

For publication, the Census Bureau aggregated HDF into a large table set called the 2010 Census Summary File 1 (SF1), which also includes all tables released as part of the 2010 Redistricting Data (P.L. 94-171) Summary File and the 2010 Advanced Group Quarters Summary File. Table 2 shows the 34 tables from SF1 used in our microdata reconstruction. The total number of linearly independent statistics, counting only blocks and tracts with positive population, is 5.0 billion.

**Table 2.**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Panel A: Tabulated at the Census Block Level | | | | | | | |
| P1 | P6 | P7 | P8 | P9 | P10 | P11 | P12 |
| P14 | P12A | P12B | P12C | P12D | P12E | P12F | P12G |
| P12H | P12I | | | | | | |
| Panel B: Tabulated at the Census Tract Level | | | | | | | |
| PCT12 | PCT12A | PCT12B | PCT12C | PCT12D | PCT12E | PCT12F | PCT12G |
| PCT12H | PCT12I | PCT12J | PCT12K | PCT12L | PCT12M | PCT12N | PCT12O |
| Source: 2010 Summary File 1 technical documentation *(34)*. | | | | | | | |

Tables from 2010 Summary File 1 used in the reconstruction experiments.

The schema used to encode age in the published data depends on the geographic level. At the tract level, age was coded in single years 0 to 99, then in intervals 100–104, 105–109, and 110 or older (103 categories). At the block level, age was coded in single years 0 to 21, then in the following intervals: 22–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–61, 62–64, 65–66, 67–69, 70–74, 75–79, 80–84, 85 or older (38 categories). In all analyses we refer to the CEF encoding as exact age, denoted as the feature *age*, and the block encoding as binned age, denoted as the feature *agebin*. Because the tract encoding has only 103 categories compared to the CEF encoding of 111, we cannot use any published data to inform single-year ages above 99; however, we still use the 111 category CEF encoding in all exact-age statistics. Note that *agebin* is nested within *age* so that any agreement on *age* implies agreement on *agebin*. Our algorithms exploit this nesting.

Finally, we used a commercial database, designated COMRCL, created by combining extracts originally purchased from four providers between 2009 and 2011.[vii] We harmonized the feature sets for these data to match the CEF. *Name* and *address* were mapped to *pik* and MAFID, respectively, using the same vintages of the Master Address File (MAF) and PVS that were used for the CEF and HDF. The components of birth date were mapped to *age* as of April 1, 2010, which is the 2010 Census reference date. We geocoded MAFID to *block* using the 2010 Census tabulation geography. We also created a special extract from the CEF, called $\text{CEF}_{atkr}$, that contained the same features as the commercial data. Because the quality of external data increased since 2010, we use $\text{CEF}_{atkr}$ to model the outcome of an attacker armed with better name, address, sex, and birth date information than COMRCL. Table 1 shows the feature sets for COMRCL and $\text{CEF}_{atkr}$.

For both the COMRCL and $\text{CEF}_{atkr}$ data, our reidentification experiments require that we use data-defined records, meaning that the values of features on that record were sufficiently complete to allow PVS to generate a *pik* for that record. There are 289.1 million unduplicated data-defined records in COMRCL from a universe of about 400 million that includes many duplicates. For the CEF this means that all whole-person census imputation records and some partial-response records were eliminated from the universe.[viii] There are 276.0 million data-defined records in the CEF from a population of 308.7 million. Table S1 shows the overlap of data-defined persons in COMRCL and CEF on the {*pik*, *block*, *sex*, *agebin*} feature set.

### *Reconstruction Methodology*

We define database reconstruction as any attempt to re-create the record-level image from which a set of published statistics was originally calculated *(36)*. Database reconstruction attempts to reverse engineer the confidential input data used in a statistical publication system with the goal of making the reconstruction as close as possible to the confidential data. This is the same definition used in *(3, 31, 37, 38)*. Since SF1 was tabulated from the confidential HDF, we reconstruct HDF; however, when assessing the correctness of reidentifications from our reconstruction, we compare it to the confidential CEF because no SDL treatments were applied to CEF.

We performed two distinct reconstruction experiments. The first, designated $\text{rHDF}_{b,t}$, used the information from all SF1 tables shown in Table 2. The second, designated $\text{rHDF}_{b}$, used only the information from the census block-level tables shown in Panel A of Table 2. This design allows us to measure the incremental contribution of the tract-level tables and to illustrate that adding tables improves the reconstruction materially. Since we used only 34 of the hundreds of published census block and tract-level tables *(34, chapter 5)*, there is great scope to reconstruct many other personal or household features beyond the five we used. The feature sets for the two reconstructed databases are shown in Table 1.

The reconstruction overview section of the supplementary methods text gives a linear algebra summary of the equation systems used for our reconstruction experiments. We implemented the reconstructions using integer programs that express the relation between each published statistic and aggregations of record types that contribute to that statistic. The schema for the binary variables that represent each allowable record and the equations for the objective function, tract-level constraints, and block-level constraints for rHDF$_{b,t}$ and rHDF$_b$ are given in the supplementary methods details section on the integer programming models and in Tables S2 and S3. These integer programs were solved using Gurobi™ convex optimization software. The complete set of linear program files for the reconstruction, including code to create all inputs from SF1, solve the integer programs, and verify the solutions, is contained in the public replication archive (Data S1).

*Solution Variability*

Our solutions for rHDF$_{b,t}$ and rHDF$_b$ are not unique *(4, 5)*; however, we can upper-bound the amount of solution variability in both reconstructions. Our method defines a statistic called *solvar* that can be interpreted as an upper bound on the percentage of records that could change in any feasible solution to the rHDF$_{b,t}$ or rHDF$_b$ reconstructions assessed using the block-level feature set {*block*, *sex, agebin*, *race, ethnicity*}. When *solvar* is zero, the reconstruction is perfect under the block-level feature set. There exists one, and only one, solution. When *solvar* is, say, 10%, then at most 10% of the reconstructed records could change on a single bit in an alternative solution, again using the block-level feature set. For a complete discussion of the solution variability methodology, including the integer program, see that section of the supplementary methods details. The public replication archive (Data S1) includes all programming and data artifacts for the solution variability analysis.

*Reconstruction Assessment*

We measure agreement between the two reconstructed databases, rHDF$_{b,t}$ and rHDF$_b$, and the two confidential databases, CEF and HDF, using both exact age and binned age. Algorithms 1 and 2 in the supplementary methods details define the match and agreement functions. There are two input databases, designated *L* and *R*. The match function loops through every record of *L* looking for exact agreement of the designated features in the designated schema in *R*. When a match occurs, the records in *L* and *R* are moved to the match set and removed from both *L* and *R*. Thus, the match function tries to link every record in *L* to records in *R* that have not already been matched. The agreement function invokes the match function twice. First, it tests for agreement on exact age. Then, on the second pass, it tests for agreement on binned age using the residual *L* and *R* files from the first pass. Since an exact-age match implies a binned-age match, the agreement function permits assessment for both age schemas.

### *Reidentification Methodology*

Putative reidentifications are those from which the attacker attempts to infer *race* and *ethnicity* for a record already in their universe. We used the common features in the reconstructed data (either rHDF$_{b,t}$ or rHDF$_b$) and the simulated attacker data (either COMRCL or CEF$_{atkr}$) to perform a textbook record linkage attack (*11*, *Chapter 5*) that enhanced the attacker data with features {*race, ethnicity*} from the reconstructed data that were not included in the attacker data feature set. Putative reidentification only involves matching on {*block*, *sex*, *age*} or {*block*, *sex*, *agebin*}, not other features. A successfully enhanced attacker data record is called a putative reidentification. The "Putative" rows of Table 1 provide the schemas for putative reidentifications based on rHDF$_{b,t}$ and rHDF$_b$. We used the same record linkage technology to match all features—not just the so-called pseudo-identifiers *block*, *sex*, and *age* (or *agebin*)—in the enhanced attacker data to a record with the same values of the features in CEF. Successful linkage of an enhanced attacker data record to a confidential record in the CEF is called a confirmed reidentification.[ix] The “Confirmed” rows of Table 1 provide the schemas for a confirmed reidentification based on rHDF$_{b,t}$ and rHDF$_b$, respectively.

For confirmed reidentifications, the attacker, presumed to know name, address, sex and age, learns information about census respondents that was previously not available—namely, self-reported race and ethnicity. Other attacks, not considered here, could include identifying household characteristics like lease occupancy violations, same-sex couples, mixed-race households, transgender individuals (when sex does not match external data), and other characteristics that invite harassment in polarized political climates. In small populations with uncommon characteristics, for example persons reporting race and ethnicity that are not the predominant race and ethnicity in a census block, the attacker learns race and ethnicity only because the target respondent’s data were used in specific SF1 tabulations and not because that respondent was statistically similar to others in the geography. That is, the inference for vulnerable populations from the confirmed reidentification is not LOO generalizable inference. It is a confidentiality breach because it depends entirely on using that person’s actual census response.

*Algorithms Implementing Reidentification*

Algorithm 3 in the supplementary methods specifies the putative reidentification procedure, again using arbitrary *L* and *R* input files with the appropriate features. As in Algorithm 2, there are two passes of the data. Pass 1 finds putative reidentifications under the exact-age schema and removes the successful matches from both *L* and *R*. Pass 2 finds the putative reidentifications under the binned-age schema using only the residual records from pass 1. Because exact-age putative reidentification implies binned-age putative reidentification, Algorithm 3 permits calculation of statistics for *age* and *agebin*. The output of Algorithm 3 is the attacker’s data enhanced with the extra features from the reconstructed data for all successful putative reidentifications using either age schema.

Algorithm 4 in the supplementary methods specifies the confirmed reidentification procedure. It takes as the input *L* file the matched file produced by Algorithm 3 (denoted $D_{X+}$ in the pseudocode). The *R* file is the CEF. Pass 1 generates all confirmed reidentifications using the exact-age schema and removes those records from *L* and *R*. Pass 2 generates the additional confirmed reidentifications using the binned-age schema. Because exact-age confirmed reidentifications imply binned-age confirmations, Algorithm 4 permits assessment using both age schemes.

*Reidentification Baselines*

First, we define upper-bound baselines. We use the CEF (removing the *pik* feature) and HDF themselves as the *L* input to Algorithm 3 to determine how accurate the attack would be if the CEF (without *pik*) or HDF were publicly released. These assessments upper-bound the potential disclosure risk from the reconstructed data because persons who are not population unique on the CEF feature set (without *pik*) are inherently indistinguishable from other persons with the same feature values in these experiments.

Second, we create two statistical baselines that implement alternative versions of approximate LOO generalizable inferences. We assume the attacker makes putative reidentifications (guesses) of the race-ethnicity combination from publicly released block-level tables containing only *race* × *ethnicity* (126 cells). The modal guesser (MDG) selects the mode of the block-level *race* × *ethnicity* table for everyone on the block. The proportional guesser

(PRG) randomly guesses with probabilities proportional to the counts from the block-level *race* × *ethnicity* table. While neither MDG nor PRG strictly delete each respondent from the confidential data then repeat the entire reconstruction-abetted reidentification attack, they are computationally feasible approximations that limit each respondent's influence on the statistic used to make the race-ethnicity inference. To make comparisons of MDG and PRG to rHDF$_{b,t}$ and rHDF$_b$ we limit the putative reidentifications to the same set identified using either rHDF$_{b,t}$ or rHDF$_b$, as appropriate. Hence, the guessing strategies only affect the confirmed reidentifications. The feature sets for MDG and PRG are also shown in Table 1.

*Reidentification Assessment*

We assess the number and accuracy of inferences an attacker could make on *race* and *ethnicity* based on linking the attacker's dataset (COMRCL or CEF$_{atkr}$) to the reconstructed dataset (rHDF$_{b,t}$ or rHDF$_b$) and comparing those outcomes to linking with the MDG or PRG datasets. Putative reidentification records are those from which the attacker attempts to infer *race* and *ethnicity*. The attacker's precision is the ratio of confirmed reidentifications to putative ones. For the MDG and PRG baselines, we use the same putative reidentifications as in rHDF$_{b,t}$ or rHDF$_b$, as appropriate. We define putative reidentification, confirmed reidentification, and precision rates, as follows:

$$Attacker\ Putative\ Reidentification\ Rate = 100 \times \frac{Count\ of\ Putative\ Reidentification\ Records}{Count\ of\ Attacker\ Records},$$

$$Attacker\ Confirmed\ Reidentification\ Rate = 100 \times \frac{Count\ of\ Confirmed\ Reidentification\ Records}{Count\ of\ Attacker\ Records},$$

$$Attacker\ Precision\ Rate = 100 \times \frac{Count\ of\ Confirmed\ Reidentification\ Records}{Count\ of\ Putative\ Reidentification\ Records}.$$

## Results

### Reconstruction Results and Discussion

Table S4 shows the cumulative distribution of *solvar*, which is always assessed using the {*block, sex, agebin, race, ethnicity*} feature set. 70% of all blocks, 97.2 million persons, have zero solution variability. The reconstructed records for those individuals are guaranteed to match their confidential HDF records in the binned-age schema. The cumulative *solvar* for all census blocks, containing all 308.7 million persons, is just 10.0%, meaning that in any other reconstruction solution for either rHDF$_b$ or rHDF$_{b,t}$ no more than 10.0% of all records could differ from their HDF record on even a single feature, evaluated on the binned-age schema.[x] This result implies that the record-level image for the entire U.S. population of the features used to create the census tract and block-level data shown in Table 2 is essentially an exact copy of HDF on the binned-age schema. Thus, the SF1 data shown in Table 2 are equivalent to the microdata HDF records for the census block-level (rHDF$_b$) feature set. The release of these microdata was prohibited by the 2010 Census disclosure avoidance rules *(39)*. Permission to release the reconstructed HDF was approved in 2022 under clearance number CBDRB-FY22-DSEP-004. The public replication archive (Data S1) includes a sample of the reconstructed records and all necessary inputs and programs to reconstruct the entire 308.7 million person records for rHDF$_{b,t}$ and rHDF$_b$ and confirm the solution variability.

Table 3 shows a detailed summary of the agreement between the reconstructed and confidential data. The first column shows the input *L* and *R* data files for Algorithm 2, which computed the agreement statistics displayed. The overall agreement of the HDF itself with the CEF is 96.3% for exact-age and 94.4% for binned-age. Hence, 96.4% is an upper bound on the overall agreement possible between the reconstructed data and the CEF. For the binned-age schema, rHDF$_{b,t}$ achieves 91.9% agreement with the CEF and 95.2% agreement with the HDF, confirming our claim that these data are an extremely accurate image of the HDF under the binned-age schema. The 48.5% agreement between rHDF$_{b,t}$ and HDF shows that the reconstructed data are also a very accurate image of HDF on the exact-age schema because the uncertainty about age is constrained by the 95.2% agreement on binned-age. In addition, when *solvar* is zero for a block containing an rHDF$_{b,t}$ record, and the associated rHDF$_{b}$ record is unique in that block, an attacker learns with certainty that the rHDF$_{b,t}$ is also population unique in HDF even if there remains some uncertainty about exact age.

**Table 3.**

| Data (*L*-*R* in Algorithm 2) | Block Population Range | Population | Agreement | | Agreement Percentage | |
|---|---:|---:|---:|---:|---:|---:|
| | | | Exact Age | Binned Age | Exact Age | Binned Age |
| HDF-CEF | All | 308,746 | 297,200 | 297,600 | 96.3 | 96.4 |
| rHDF$_{b,t}$-CEF | All | 308,746 | 143,800 | 283,600 | 46.6 | 91.9 |
| rHDF$_{b}$-CEF | All | 308,746 | 132,200 | 276,900 | 42.8 | 89.7 |
| rHDF$_{b,t}$-HDF | All | 308,746 | 149,600 | 294,000 | 48.5 | 95.2 |
| rHDF$_{b}$-HDF | All | 308,746 | 136,500 | 286,700 | 44.2 | 92.9 |
| HDF-CEF | 1-9 | 8,070 | 5,866 | 5,973 | 72.7 | 74.0 |
| rHDF$_{b,t}$-CEF | 1-9 | 8,070 | 2,419 | 5,971 | 30.0 | 74.0 |
| rHDF$_{b}$-CEF | 1-9 | 8,070 | 2,325 | 5,968 | 28.8 | 74.0 |
| rHDF$_{b,t}$-HDF | 1-9 | 8,070 | 3,492 | 8,063 | 43.3 | 99.9 |
| rHDF$_{b}$-HDF | 1-9 | 8,070 | 3,275 | 8,056 | 40.6 | 99.8 |
| HDF-CEF | 10-49 | 67,598 | 63,460 | 63,580 | 93.9 | 94.1 |
| rHDF$_{b,t}$-CEF | 10-49 | 67,598 | 29,500 | 62,870 | 43.6 | 93.0 |
| rHDF$_{b}$-CEF | 10-49 | 67,598 | 28,990 | 62,330 | 42.9 | 92.2 |
| rHDF$_{b,t}$-HDF | 10-49 | 67,598 | 31,810 | 66,760 | 47.1 | 98.8 |
| rHDF$_{b}$-HDF | 10-49 | 67,598 | 30,860 | 66,090 | 45.6 | 97.8 |
| HDF-CEF | 50-99 | 69,073 | 66,560 | 66,630 | 96.4 | 96.5 |
| rHDF$_{b,t}$-CEF | 50-99 | 69,073 | 31,280 | 64,330 | 45.3 | 93.1 |
| rHDF$_{b}$-CEF | 50-99 | 69,073 | 30,600 | 63,130 | 44.3 | 91.4 |
| rHDF$_{b,t}$-HDF | 50-99 | 69,073 | 32,560 | 66,570 | 47.1 | 96.4 |
| rHDF$_{b}$-HDF | 50-99 | 69,073 | 31,540 | 65,230 | 45.7 | 94.4 |
| HDF-CEF | 100-249 | 80,021 | 78,370 | 78,420 | 97.9 | 98.0 |
| rHDF$_{b,t}$-CEF | 100-249 | 80,021 | 36,840 | 73,810 | 46.0 | 92.2 |
| rHDF$_{b}$-CEF | 100-249 | 80,021 | 34,690 | 71,940 | 43.4 | 89.9 |
| rHDF$_{b,t}$-HDF | 100-249 | 80,021 | 37,590 | 75,190 | 47.0 | 94.0 |
| rHDF$_{b}$-HDF | 100-249 | 80,021 | 35,160 | 73,180 | 43.9 | 91.4 |
| HDF-CEF | 250-499 | 42,911 | 42,320 | 42,340 | 98.6 | 98.7 |
| rHDF$_{b,t}$-CEF | 250-499 | 42,911 | 20,750 | 39,240 | 48.3 | 91.4 |
| rHDF$_{b}$-CEF | 250-499 | 42,911 | 18,170 | 37,960 | 42.3 | 88.5 |
| rHDF$_{b,t}$-HDF | 250-499 | 42,911 | 20,970 | 39,680 | 48.9 | 92.5 |
| rHDF$_{b}$-HDF | 250-499 | 42,911 | 18,270 | 38,330 | 42.6 | 89.3 |
| HDF-CEF | 500-999 | 27,029 | 26,720 | 26,740 | 98.9 | 98.9 |

| | | | | | | |
|---|---|---|---|---|---|---|
| rHDF$_{b,t}$-CEF | 500-999 | 27,029 | 14,220 | 24,550 | 52.6 | 90.8 |
| rHDF$_{b}$-CEF | 500-999 | 27,029 | 11,380 | 23,480 | 42.1 | 86.9 |
| rHDF$_{b,t}$-HDF | 500-999 | 27,029 | 14,310 | 24,750 | 52.9 | 91.6 |
| rHDF$_{b}$-HDF | 500-999 | 27,029 | 11,410 | 23,640 | 42.2 | 87.5 |
| HDF-CEF | 1000+ | 14,043 | 13,930 | 13,940 | 99.2 | 99.3 |
| rHDF$_{b,t}$-CEF | 1000+ | 14,043 | 8,835 | 12,870 | 62.9 | 91.7 |
| rHDF$_{b}$-CEF | 1000+ | 14,043 | 6,009 | 12,120 | 42.8 | 86.3 |
| rHDF$_{b,t}$-HDF | 1000+ | 14,043 | 8,863 | 12,940 | 63.1 | 92.1 |
| rHDF$_{b}$-HDF | 1000+ | 14,043 | 6,014 | 12,170 | 42.8 | 86.7 |

Notes: Counts in thousands. 2010 Census exact block populations are public data; therefore, the population column is not rounded. Other counts rounded to four significant digits to conform to current disclosure avoidance rules. Agreement percentages use the population in the census blocks included for that row.

Reconstruction agreement statistics.

Table 3 also shows that block population size plays an important role in the level of agreement between the reconstructed and confidential microdata. The HDF-CEF agreement is much lower for the lowest-population blocks relative to the largest (74.0% vs. 99.3%), reflecting the higher probability that SDL was applied to low-population census blocks (our attacks did not try to undo the SDL). However, agreement between rHDF$_{b,t}$ and HDF is almost perfect (99.9%) in terms of binned age for the smallest blocks, resulting in rHDF$_{b,t}$ agreement with the CEF that almost matches the HDF-CEF agreement for the blocks with the smallest populations. The contributions of errors due to the SDL methodology and those due to reconstruction work in opposite directions as block size increases. The binned-age agreement rates for rHDF$_{b,t}$-CEF are roughly constant (between 90.8% and 93.1%) for blocks with 10 or more persons. However, while the rHDF$_{b}$ reconstruction agreement rates to CEF and HDF are very similar to those for rHDF$_{b,t}$ for the lowest-population blocks, they are noticeably worse for the most populous blocks, indicating that adding tract-level information is important in reconstructing records in populous census blocks. Overall, the results in Table 3 confirm that reconstruction produces an extremely accurate image of HDF and a very accurate image of CEF using only the SF1 data shown in Table 2 when considering the feature set {*block*, *sex*, *agebin*, *race*, *ethnicity*}.

Two additional points merit attention. First, *solvar* can be computed using only public data, meaning that an attacker could use *solvar* to target particular census blocks for which the reconstruction is unique—access to the confidential HDF or CEF is not required. Second, inferences about populations in small census blocks tend to be more sensitive to the absence of one person's census record because leaving out a unique or nearly unique record type in these blocks is much more likely to change an inference than leaving out one of many records of the same type. This phenomenon is even stronger in blocks with zero solution variability because in these blocks a record unique in rHDF$_{b}$ or rHDF$_{b,t}$ is provably unique in the HDF, while for blocks with positive solution variability, this may not be the case. Table S5 shows the distribution of persons who are population unique by census block size for all blocks and for blocks with zero solution variability. Data S2 and the replication archive (Data S1) contain an Excel workbook with a selection of 29 census tracts from the 949 for which every block had zero solution variability. Indicators show which records are unique on the rHDF$_{b}$ feature set for {*block*, *sex*, *agebin*} and unique on those features plus {*race*, *ethnicity*} in the reconstructed data. If there is zero solution variability, then the attacker knows the record is unique in the HDF as well. A record that is unique on the rHDF$_{b}$ schema must also be unique on the rHDF$_{b,t}$ schema. No confirmed reidentification is required to learn this uniqueness and the associated feature values. Traditional SDL considers this exposure of population uniqueness in released data *de facto* prohibited disclosure: "[i]f a unit is population unique then disclosure will occur if a snooper knows it is unique" *(11, pp. 42-43)*.

*Reidentification Results and Discussion*

Table 4 presents the statistics for the putative, confirmed, and precision rates for all persons in the 2010 Census and Table S6 shows the distribution by census block size. Table 4 results are refinements of those first released in 2019 *(24)*. They show that when the attacker uses COMRCL, the reconstruction rHDF$_{b,t}$ produces 166.1 million putative reidentifications (57.5% of the data-defined population) of which 68.5 million are confirmed (23.7% of the data-defined population) with a precision of 41.2%. When the attacker uses high-quality input data CEF$_{atkr}$, the reconstruction rHDF$_{b,t}$ yields 267.8 million putative reidentifications (97.0% of the data-defined population) of which 208.5 million are confirmed (75.5% of the data-defined population) with a precision of 77.9%.

The Census Bureau released similar reidentification results between 2019 and 2022 based on earlier versions of the models presented in this paper. Some scholars noted that baselines similar to MDG and PRG could produce reidentifications apparently comparable to those of rHDF$_{b,t}$ *(6, 7)*. The rows MDG and PRG in the COMRCL panel confirm that claim.[xi] By construction, these two strategies have the same overall putative reidentifications as rHDF$_{b,t}$, and their confirmation and precision rates are also comparable. This misleading similarity requires using leave-one-out reasoning to resolve, which we do below.

**Table 4.**

| Data (*L* in Algorithm 3) | Population | Putative | Putative Percentage | Confirmed | Confirmed Percentage | Precision Percentage |
|---|---|---|---|---|---|---|
| | Attacker (*R* in Algorithm 3) COMRCL | | | | | |
| CEF | 289,100 | 167,500 | 57.9 | 82,760 | 28.6 | 49.4 |
| HDF | 289,100 | 166,100 | 58 | 80,540 | 27.9 | 48.5 |
| rHDF$_{b,t}$ | 289,100 | 166,100 | 57.5 | 68,480 | 23.7 | 41.2 |
| rHDF$_{b}$ | 289,100 | 166,100 | 58 | 67,450 | 23.3 | 40.6 |
| MDG | 289,100 | 166,100 | 57.5 | 76,270 | 26.4 | 45.9 |
| PRG | 289,100 | 166,100 | 57.5 | 66,260 | 22.9 | 39.9 |
| | Attacker (*R* in Algorithm 3) CEF$_{atkr}$ | | | | | |
| CEF | 276,000 | 276,000 | 100.0 | 237,500 | 86.1 | 86.1 |
| HDF | 276,000 | 267,800 | 97.0 | 228,400 | 82.8 | 85.3 |
| rHDF$_{b,t}$ | 276,000 | 267,800 | 97.0 | 208,500 | 75.5 | 77.9 |
| rHDF$_{b}$ | 276,000 | 267,800 | 97.0 | 203,100 | 73.6 | 75.9 |
| MDG | 276,000 | 267,800 | 97.0 | 205,100 | 74.3 | 76.6 |
| PRG | 276,000 | 267,800 | 97.0 | 177,700 | 64.4 | 66.3 |
| Counts in thousands rounded to four significant digits to conform to current disclosure avoidance rules. The distribution by census block size is shown in Table S6. | | | | | | |

Putative reidentification, confirmed reidentification, and precision rates for all data-defined persons in the 2010 Census.

Surprisingly, releasing the CEF itself with the full feature set in Table 1 (except *pik*) would produce only a small increase in the putative, confirmed, and precision rates compared to rHDF$_{b,t}$, as shown in the first row of the COMRCL panel.[xii] 2010-era commercial data did not align well with the data collected in the 2010 Census. This nonalignment is further elaborated in the supplementary text and Table S7. If the attacker used high-quality input data, as in CEF$_{atkr}$, releasing the HDF with the feature set shown in Table 1 would result in exactly the same putative reidentifications as either rHDF$_{b,t}$ or rHDF$_{b}$, showing once again how accurate the reconstructed data are. The confirmation and precision rates for HDF are marginally higher than those for rHDF$_{b,t}$, rHDF$_{b}$ and MDG and substantially better than PRG.

Although rHDF$_{b,t}$ and rHDF$_{b}$ perform comparably to the MDG baseline, and only somewhat better than PRG, on average for the whole nation, the reconstructed HDFs are substantively superior in reidentifying vulnerable populations—those whose features are different from their neighbors. Table 5, which shows results for persons who are not in the modal *race* × *ethnicity* cell within their census block by block population, illustrates this difference sharply. For both the COMRCL and CEF$_{atkr}$ attacker data, the table shows that rHDF$_{b,t}$ is much better than MDG at predicting the *race* and *ethnicity* features for nonmodal individuals. The modal guesser's precision is between 0.2% and 8.8%, averaging only 1.1% (COMRCL) or 0.9% (CEF$_{atkr}$) for this population.[xiii] The proportional guesser's precision is between 14.1% and 31.8%, averaging 15.7% (COMRCL) and 16.0% (CEF$_{atkr}$). By contrast, the precision of rHDF$_{b,t}$ varies between 21.0% and 86.0%, averaging 41.0% for COMRCL and 43.3% for CEF$_{atkr}$. Importantly, the precision of the rHDF$_{b,t}$ attack exceeds 50% for any nonmodal person living in a census block with population less than 100 persons, 13.2 million people.[xiv] Furthermore, for the 3.4 million nonmodal persons who are population unique in blocks with zero solution variability, the precision of the rHDF$_{b,t}$ attack is between 91.2% and 95.2%, while MDG and PRG achieve 3.2% and 20.2%, respectively, at best. (See Table S8.) These inferences about the nonmodal population violate LOO reasoning. They are not generalizable scientific inferences. They are only possible because that person's record was included in the confidential HDF used to produce the SF1 tables.

**Table 5.**

| | | Attacker (*R* in Algorithm 3): COMRCL | | | Attacker (*R* in Algorithm 3): CEF$_{atkr}$ | | |
|---|---|---|---|---|---|---|---|
| Data (*L* in Algorithm 3) | Block Population Range | Putative | Confirmed | Precision Percentage | Putative | Confirmed | Precision Percentage |
| CEF | All | 16,340 | 9,746 | 59.7 | 65,850 | 42,070 | 63.9 |
| HDF | All | 15,780 | 8,967 | 56.8 | 62,530 | 38,120 | 61.0 |
| rHDF$_{b,t}$ | All | 14,990 | 6,147 | 41.0 | 62,810 | 27,180 | 43.3 |
| rHDF$_{b}$ | All | 14,780 | 5,514 | 37.3 | 62,810 | 23,990 | 38.2 |
| MDG | All | 15,780 | 170 | 1.1 | 62,530 | 580 | 0.9 |
| PRG | All | 15,780 | 2,473 | 15.7 | 62,530 | 10,000 | 16.0 |
| CEF | 1-9 | 148 | 143 | 97.0 | 480 | 472 | 98.3 |
| HDF | 1-9 | 92 | 81 | 87.7 | 276 | 249 | 90.2 |
| rHDF$_{b,t}$ | 1-9 | 90 | 75 | 83.7 | 279 | 240 | 86.0 |
| rHDF$_{b}$ | 1-9 | 89 | 74 | 82.7 | 279 | 236 | 84.7 |
| MDG | 1-9 | 92 | 8 | 8.8 | 276 | 20 | 7.2 |
| PRG | 1-9 | 92 | 29 | 31.7 | 276 | 88 | 31.8 |
| CEF | 10-49 | 2,621 | 2,242 | 85.6 | 9,545 | 8,713 | 91.3 |
| HDF | 10-49 | 2,337 | 1,865 | 79.8 | 7,971 | 6,904 | 86.6 |
| rHDF$_{b,t}$ | 10-49 | 2,199 | 1,435 | 65.3 | 8,084 | 5,777 | 71.5 |
| rHDF$_{b}$ | 10-49 | 2,159 | 1,344 | 62.3 | 8,082 | 5,397 | 66.8 |
| MDG | 10-49 | 2,337 | 59 | 2.5 | 7,971 | 184 | 2.3 |
| PRG | 10-49 | 2,337 | 444 | 19.0 | 7,971 | 1,587 | 19.9 |
| CEF | 50-99 | 3,745 | 2,748 | 73.4 | 13,740 | 11,200 | 81.5 |
| HDF | 50-99 | 3,600 | 2,527 | 70.2 | 12,790 | 10,060 | 78.6 |
| rHDF$_{b,t}$ | 50-99 | 3,355 | 1,688 | 50.3 | 12,900 | 7,221 | 56.0 |
| rHDF$_{b}$ | 50-99 | 3,296 | 1,525 | 46.3 | 12,900 | 6,422 | 49.8 |
| MDG | 50-99 | 3,600 | 47 | 1.3 | 12,790 | 157 | 1.2 |
| PRG | 50-99 | 3,600 | 576 | 16.0 | 12,790 | 2,111 | 16.5 |
| CEF | 100-249 | 4,775 | 2,797 | 58.6 | 18,670 | 12,460 | 66.8 |
| HDF | 100-249 | 4,718 | 2,700 | 57.2 | 18,210 | 11,870 | 65.2 |
| rHDF$_{b,t}$ | 100-249 | 4,457 | 1,706 | 38.3 | 18,260 | 7,645 | 41.9 |
| rHDF$_{b}$ | 100-249 | 4,391 | 1,496 | 34.1 | 18,260 | 6,553 | 35.9 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| MDG | 100-249 | 4,718 | 35 | 0.7 | 18,210 | 132 | 0.7 |
| PRG | 100-249 | 4,718 | 706 | 15.0 | 18,210 | 2,798 | 15.4 |
| CEF | 250-499 | 2,531 | 1,063 | 42.0 | 10,970 | 5,275 | 48.1 |
| HDF | 250-499 | 2,523 | 1,047 | 41.5 | 10,870 | 5,142 | 47.3 |
| rHDF$_{b,t}$ | 250-499 | 2,430 | 687 | 28.3 | 10,880 | 3,337 | 30.7 |
| rHDF$_{b}$ | 250-499 | 2,402 | 591 | 24.6 | 10,880 | 2,807 | 25.8 |
| MDG | 250-499 | 2,523 | 12 | 0.5 | 10,870 | 51 | 0.5 |
| PRG | 250-499 | 2,523 | 359 | 14.3 | 10,870 | 1,586 | 14.6 |
| CEF | 500-999 | 1,677 | 537 | 32.0 | 7,846 | 2,735 | 34.9 |
| HDF | 500-999 | 1,675 | 532 | 31.8 | 7,812 | 2,690 | 34.4 |
| rHDF$_{b,t}$ | 500-999 | 1,635 | 383 | 23.4 | 7,813 | 1,945 | 24.9 |
| rHDF$_{b}$ | 500-999 | 1,621 | 331 | 20.4 | 7,813 | 1,664 | 21.3 |
| MDG | 500-999 | 1,675 | 6 | 0.4 | 7,812 | 28 | 0.4 |
| PRG | 500-999 | 1,675 | 236 | 14.1 | 7,812 | 1,116 | 14.3 |
| CEF | 1000+ | 840 | 216 | 25.8 | 4,602 | 1,213 | 26.4 |
| HDF | 1000+ | 840 | 215 | 25.6 | 4,595 | 1,203 | 26.2 |
| rHDF$_{b,t}$ | 1000+ | 827 | 174 | 21.0 | 4,595 | 1,017 | 22.1 |
| rHDF$_{b}$ | 1000+ | 822 | 154 | 18.7 | 4,595 | 911 | 19.8 |
| MDG | 1000+ | 840 | 2 | 0.2 | 4,595 | 8 | 0.2 |
| PRG | 1000+ | 840 | 122 | 14.6 | 4,595 | 717 | 15.6 |

Notes: Counts in thousands rounded to four significant digits to conform to current disclosure avoidance rules. COMRCL and CEF$_{atkr}$ use only data-defined records. Comparable statistics for modal persons are in Table S9.

Putative reidentifications, confirmed reidentifications, and precision rates for nonmodal persons.

### Protecting the 2020 Census from This Attack

The main results from the 2020 Census will be released on May 25, 2023. These publications were protected using the zero-concentrated differential privacy framework implemented via the discrete Gaussian mechanism (*40*). The complete privacy-loss accounting was released April 3, 2023 (*41,42*). A condition of the Census Bureau's release of the 2020 Census data was that the DAS defend the 2020 Demographic and Housing Characteristics (DHC) File (successor to SF1) from the attack described in this paper. We could only do that once the DAS was completed and final production settings approved, which occurred in November and December 2022.

Using those publication settings, we analyzed the tables from the demonstration 2010 DHC, the analogue of the 2010 SF1 and also released on April 3, 2023, by extracting the table set equivalent to those in Table 2 and repeating the entire reconstruction-abetted reidentification attack. We call these results rMDF$_{b,t}$ because they are directly analogous to rHDF$_{b,t}$. For completeness, and because a version of this file will be released publicly for the 2020 Census, we also analyzed the microdata representation of the differentially private table set, internally called the Microdata Detail File (MDF) and known externally as the 2010 Demonstration Data Product Suite Privacy-Protected Microdata File (also released April 3, 2023). As shown in *(40)*, the MDF solves a complex, multistage optimization problem to produce the microdata records that best fit the tabular summaries produced by the application of differentially private mechanisms to statistics computed from the CEF. That is, the MDF solves the reconstruction problem from noisy output, but not using the method in *(3)*. The MDF is, therefore, directly analogous to the HDF. It is the microdata input to all tables. The feature sets for MDF and rMDF$_{b,t}$ are shown in the final rows of Table 1.

**Table 6.**

| | Nonmodal Persons | | Population Unique Nonmodal Persons | |
|---|---|---|---|---|
| Data (*L* in Algorithm 3) | COMRCL Precision | CEF$_{atkr}$ Precision | COMRCL Precision | CEF$_{atkr}$ Precision |
| CEF | 81.9 | 87.9 | 97.4 | 100.0 |
| HDF | 74.5 | 81.1 | 93.0 | 95.6 |
| rHDF$_{b,t}$ | 61.6 | 68.5 | 91.2 | 95.2 |
| rHDF$_{b}$ | 57.2 | 63.5 | 90.6 | 92.5 |
| rMDF$_{b,t}$ | 15.8 | 18.9 | 15.8 | 21.8 |
| MDF | 15.8 | 18.9 | 15.8 | 21.8 |
| MDG | 1.9 | 1.7 | 1.9 | 2.5 |
| PRG | 16.0 | 17.2 | 16.0 | 20.2 |
| Notes: Precision rates stated as percentages of putative reidentifications see Table S8 for details. Attacker database (COMRCL or CEF$_{atkr}$) is file *R* in Algorithm 3. Shaded rows are outputs from the 2020 DAS. | | | | |

Precision rates for all zero *solvar* nonmodal persons and population unique zero *solvar* nonmodal persons including results using the 2020 Census Disclosure Avoidance System applied to the 2010 Census.

Table 6 shows that output from the 2020 DAS applied to the 2010 Census reduces the reidentification precision of zero *solvar* records for nonmodal persons and the population unique persons among those with zero *solvar* to rates comparable to the baseline PRG, indicating that the 2020 DAS essentially eliminates non-LOO confidentiality-breaching inferences—those that depend strongly on the use of actual census responses for sensitive populations. Table S10 shows the agreement rates of rMDF$_{b,t}$ and MDF with the CEF. The agreement of MDF with CEF is only 36.7% on average. Reconstruction attacks based on the published DHC cannot produce a more accurate image of the CEF than the MDF. Table S10 also shows that the agreement of rMDF$_{b,t}$ and MDF with the CEF increases monotonically as the block population increases, confirming that the quality of LOO or generalizable inferences increases as the population under study increases.

Table S11 confirms that the 2020 DAS reduces the precision of reidentifications for all nonmodal persons, not just those with zero *solvar*, from 41.0% (rHDF$_{b,t}$-COMRCL) to 18.6% (rMDF$_{b,t}$-COMRCL) and from 43.3% (rHDF$_{b,t}$-CEF$_{atkr}$) to 20.3% (rMDF$_{b,t}$-CEF$_{atkr}$) overall.

Much more importantly, the reidentification precision never exceeds 25.5% even for those living in blocks with populations less than 10, where $rHDF_{b,t}$ has precision of 86.0%. Tables S12 (all data-defined persons) and S13 (all modal persons) show that this reduction in precision for sensitive populations does not substantially impede LOO inferences—modal person reidentification precisions fell, on average, from 88.5% ($rHDF_{b,t}$-COMRCL) to 77.3% ($rMDF_{b,t}$-COMRCL) and from 88.5% ($rHDF_{b,t}$-$CEF_{atkr}$) to 78.9% ($rMDF_{b,t}$-$CEF_{atkr}$). Tables S11-S13 also show that the microdata image produced by the DAS (MDF) has essentially the same putative, confirmed and precision rates as the table image ($rMDF_{b,t}$), implying that a reconstruction of MDF from $rMDF_{b,t}$ with zero solution variability in all census blocks would have the same statistical properties and disclosure risk as the tables, which Table 6 confirms. Either could be safely released. Data S3 and the replication archive (Data S1) contain an Excel workbook with records for the same 29 census tracts as Data S2 for comparison purposes.

## Conclusions

Our experiments confirm that it is possible to create an extremely accurate reconstruction (95.2% agreement on the binned-age schema) of the underlying confidential HDF microdata from publicly available sources, effectively undoing confidentiality protections from aggregation and equivalent to releasing the HDF with the $rHDF_b$ feature set. For almost half the HDF records, the reconstruction is also equivalent to releasing the confidential $rHDF_{b,t}$ feature set, effectively undoing the protection of age binning. Using binned age, there is no reconstruction uncertainty for more than two-thirds of census blocks (97 million persons), meaning that the records are the exact image of the HDF for the $rHDF_b$ feature set, leaving swapping and group quarters synthetic data protections as the only source of uncertainty for correctness relative to the CEF.

Swapping does affect the accuracy of the reconstruction relative to the CEF, especially in the smallest-population blocks, but accuracy is still very high overall. The attacker's ability to reconstruct the confidential HDF records with very high reliability, effectively recreating the $rHDF_b$ features outside the Census Bureau firewall, violated the disclosure avoidance standards for the 2010 Census whether or not such reconstruction enabled reidentification, and this would also have been true had the 2020 Census used the 2010 methods for its tabular releases, which is why the decision to adopt the differential privacy framework was based on the reconstruction results. See the supplementary text on SDL applied to the 2010 Census for a full accounting.

When the attacker has high-quality name, address, sex, and age data, our experiments also confirm that, given the 2010 Census SDL framework, releasing microdata containing geographic identifiers for areas with average population of 50 persons (the 2010 occupied census *block* average), *sex*, and *age* is sufficient to correctly reidentify the data provided for 75.5% of the data-defined population, thus defeating protection from aggregation. Releasing *block*, *sex*, and *agebin* is sufficient to re-identify the data supplied for 73.6% of the data-defined population, thus also defeating additional protection from binning age at the block level.

While an attacker armed with only the block-level distribution of *race* × *ethnicity*, can match the U.S. average reidentification precision of $rHDF_{b,t}$ and $rHDF_b$, that attacker cannot come close to the reidentification precision from the reconstructed data for vulnerable populations—those people who differ from the typical person in their geography. The inferences enabled by the reconstructed microdata fail the leave-one-out criterion for scientific or generalizable inference—they are only possible because the vulnerable person's data were used to calculate the published summary tables. Those are confidentiality-violating inferences, and there are at least 3.4 million such inferences possible from the records that the attacker knows with certainty are population unique in the confidential HDF data. No access to those confidential data is required to make such inferences. In the worst case we examined, the attacker could infer the race and ethnicity of nonmodal persons for more than 13.2 million people with precision greater than 50%, although fieldwork or some labeled training data would be required to learn that precision. Our analysis of the differentially private framework and parameter settings used for the 2020 Census confirms that these methods defend against reconstruction-abetted reidentification attacks by lowering the precision on vulnerable populations to well below 50% and usually well below 25%.

## Notes

[i] Through the text, we use italics to indicate specific features of the data whose schemas remain fixed. Those schemas are defined in the methods section.

[ii] In this context, the mathematical property of composition means that if the methods are both used on different products from the same confidential input, the resulting publications still protect confidentiality—one method does not undo the protection of the other.

[iii] NP-hard means at least as algorithmically complex as an NP-complete problem—there is no known efficient solution.

[iv] The work reported in this paper began in 2016. Preliminary results were reported at the AAAS annual meetings in 2019 *(24)*, in testimony from Abowd *(25, 26, 27)*, presentations to the Census Bureau's Scientific Advisory Committee *(28)*, and by Abowd and Hawes *(29)*. The earlier work was peer-reviewed by *(30)*. Several authors used these releases to comment on the results. See details in the supplemental text on related reconstruction studies and the relationship to differential privacy.

[v] This description is a technical simplification. We have abstracted from processing details that do not affect our study.

[vi] The use of the Census Bureau's production record-linkage system was a deliberate choice. The PVS uses a large inventory of administrative records that facilitate name and address linking for input data with different reference dates and available features. The alternative would have been to build a new record linkage system specifically for this project. However, the PVS has standardizers and workflows that have been in continuous development since the 1990s. Whether we could have developed an improved record linkage system is outside the scope of this project. To control the quality of the record linkage, we used linkages based on the 2010 Census vintage of the PVS for all name, address, sex, and age-based entity resolution. For details on that vintage of the PIK assignment algorithms, see *(33)*.

[vii] The four commercial providers were Experian Marketing Solutions Incorporated, Infogroup Incorporated, Targus Information Corporation, and VSGI LLC. These are the same data used in *(35)* except we excluded data from the Melissa Data Corporation for technical reasons.

[viii] These terms are defined in *(34)*. See *(33)* for an explanation of how they affect record linkage in the PVS and the supplemental text on 2010 Census internal databases for further details.

[ix] If the process of classifying the putative reidentifications in the reconstructed data as "correctly matched" or "incorrectly unmatched" to the external database is considered a statistical classifier, then to perform a similar exercise, an attacker external to the Census Bureau would need a labeled training sample, which might be obtained from field work or additional databases.

[x] We reconstruct the entire HDF (308.7 million records), but we only perform reidentification experiments on the data-defined population (276.0 million records). Cumulative *solvar* refers to the reconstruction accuracy and uses all records.

[xi] (*6*) estimates the probability of finding a random record in a random block, which is not the same as the reidentification precision rate. For example, that model estimates that the expected probability of finding a 50-year-old female in a random block is 57%, which has no relation to a reidentification precision rate. *(7)* uses block-level racial homogeneity rather than PRG to draw its conclusions, making them not comparable to ours.

[xii] Strictly speaking, the counterfactual is that the CEF is released in a manner such that the *name* and *address* features of the CUF are standardized by the same algorithms used by PVS so that external record linkage would produce an identifier like the *pik* feature.

[xiii] See the supplementary text on statistical baselines for the method of breaking *race* × *ethnicity* ties among the 126 cells, which explains why the precision of MDG is not exactly zero for nonmodal individuals.

[xiv] Table 3 shows that 46.9% of the total population in 2010 lived in census blocks with less than 100 persons.

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**Data and materials availability:** The public replication archive is located at https://github.com/uscensusbureau/recon_replication with instructions in Data S1. Data S4 contains Tables 1 to S13 in electronic format. The archive contains pointers to the official versions of all public data used in this paper, ancillary tables mentioned in the main and supplementary text, the complete code base, and a description of the workflow that meets current scientific best practices as defined by the American Economic Association https://aeadataeditor.github.io/. Census Bureau Data Stewardship Policy DS-027 https://www2.census.gov/foia/ds_policies/ ds027.pdf permitted the editor and referees of this journal to independently verify the correctness of the calculations done on the confidential 2010 Census and commercial data used in this paper.

## Supplementary Materials

Materials

Supplementary Text

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