The Effect of the Differential Privacy Disclosure Avoidance System Proposed by the Census Bureau on 2020 Census Products: Four Case Studies of Census Blocks in Mississippi.

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Abstract

The Census Bureau plans to introduce a new Disclosure Avoidance System known as Differential Privacy (DP) for its 2020 census data products. Using a DP demonstration product file provided by the Census Bureau, we assess the errors introduced by DP on census block data in Mississippi in the form of four case studies and find them to be substantial by type and level. We use both the May 27th 2020 DP demonstration product and the most recent, the April 28th 2021 DP demonstration product relative to our four cases studies and compare the changes. This comparison is important because the Census Bureau reports, the accuracy should improve because the privacy budget was increased in response to user complaints about poor accuracy. We find that the April 28th, 2021 release does produce more accurate data but that the level of accuracy remains unsuitable for use by those who work with small area data. Because it is likely that the results we found in Mississippi will be found in other states, our examination leads us to conclude that it is likely that the errors introduced by DP of the type and at the level found in the most recent demonstration product file we examined will render the nation's block level data essentially unusable.

Introduction

The 2020 Census attempts to count every person living in the United States and the five U.S. territories. The stated goal is to count everyone only once and in the right place. The count is mandated by the Constitution and conducted by the U.S. Census Bureau. The requirement of taking a census is one of the first things mentioned in the U.S. Constitution, which provides some indication of how important a census was to the Founding Fathers (National Research Council, 2006).

The U.S. Constitution requires an "actual enumeration" of the population every 10 years to apportion seats in the House of Representatives among the states. States and localities also use census numbers for redistricting, to draw political boundary lines for their congressional delegations, legislatures, and other government districts. The census plays an important role in guiding the distribution of $1.5 trillion in federal funding, as well as identifying needs for government services, such as schools and roads. Census statistics are the basis for a wide range of research and business decisions.

In a recent publication of the International Association of Official Statistics discussing the importance of Censuses in an international context, Everaers (2021) stated, “Population and Housing Censuses are an important cornerstone for National Statistical Systems. They provide a range of important statistics, relevant for policy-making, planning, and monitoring but also functioning as reference point and sample frame for many other national and regional statistics.” This description certainly applies to the U.S. Census. There is no single statistical resource more important than the Decennial Census.

In every census, the U.S. Census Bureau faces a trade-off between privacy protection and accuracy. According to the U.S. Census Bureau (2020d),

> “One of the most important roles that national statistical offices (NSOs) play is to carry out a national population and housing census. In so doing, NSOs have two data stewardship mandates that can be in direct opposition. Good data stewardship involves both safeguarding the privacy of the respondents who have entrusted their information to the NSOs as well as disseminating accurate and useful census data to the public.”

The preceding suggests that this is an appropriate place to discuss privacy and confidentiality, two concepts that are often used interchangeably, but are distinct. Privacy generally is used in regard to the right of an individual or organization to withhold information from others, while confidentiality is viewed as an extension of privacy in which an organization (such as the Census Bureau) that holds individual or organizational information is obligated to ensure that only authorized individuals have access to the information.

For over a century and for nearly as long as the Census Bureau has existed in its present form, it has had to balance its inherent, ingrained mission of collecting and producing high quality statistical information for the public good with a mandate to avoid disclosing information about any individual. In fact, the

Census Bureau's mission is “to serve as the nation's leading provider of quality data about its people and economy.” However, the mandate of “quality data” is tempered by an obligation to protect the privacy of Census respondents. The Census Bureau is bound by Title XIII of the United States Code. Title XIII provides the following protections to individuals and businesses (U.S. Census Bureau, no date):

- Private information is never published. It is against the law to disclose or publish any private information that identifies an individual or business such, including names, addresses (including GPS coordinates), Social Security Numbers, and telephone numbers.
- The Census Bureau collects information to produce statistics. Personal information cannot be used against respondents by any government agency or court.
- Census Bureau employees are sworn to protect confidentiality. People sworn to uphold Title XIII are legally required to maintain the confidentiality of data. Every Census Bureau employee or contractor with access to personal data is sworn for life to protect your information and understands that the penalties for violating this law are applicable for a lifetime.

As part of this balancing act, the Census Bureau has used methods to help avoid disclosure of individual census respondents for many decades. According to the U.S. Census Bureau (2018), some method of disclosure avoidance has been used by the U.S. Census Bureau since 1970. However, as the privacy protections were put in place by the Census Bureau over the past several decades, there was never the threat of distorting the data as much as DP threatens to distort the 2020 Census data, and there was never the resistance seen among data users and demographers regarding the potential use of DP in the 2020 Census (Ruggles et al., 2019). The increase in resistance among data users reflects the extent to which they fear differential privacy will distort the data to the point that it is not usable for many functions.

The Census Bureau plans to introduce a new Disclosure Avoidance System known as Differential Privacy (DP) for its 2020 census data products (Abowd, 2020, Census Bureau 2020a, 2020b, 202c, 2020d, 2020e, 2020f, and 2020g), which we describe in some detail in Appendix 1.

Ruggles et al. (2019: 406) argue that DP goes far beyond what is necessary to keep data safe under census law and precedent and because it focuses on concealing individual characteristics instead of respondent identities, DP is a blunt and inefficient instrument for disclosure control. They go on to note that because the core metric of DP does not measure the risk of identity disclosure, it cannot assess disclosure risk as defined under census law, making it untenable for optimizing the privacy/usability trade-off.

Our purpose in this paper is to assess the errors introduced by (DP) on census block data in Mississippi in the form of comparing four case studies taken from the May 27th, 2020 and April 28th, 2021 demonstration products, respectively.

Data and Methods

Mississippi is the 32nd largest state with 48,430 square miles (https://en.wikipedia.org/wiki/Mississippi). The 2010 census counted 2,967,297 persons (U.S. Census Bureau, 2012: IV-3), which yields 61.3 persons per square mile. The 2010 census organized the state into 171,778 census blocks, of which 84,750 had one or more persons, leaving 87,028 without any population. On average, there were only 17.27 persons in each of the 171,778 census blocks.[1] If we look at the 84,750 census blocks with at least one person, there were 35 persons on average in each of them. These summary statistics make Mississippi one of the states in which one would expect a high level of disclosure avoidance at the block level because there are so few people on average per block. This is a point to which we return in the final section.

The application of DP is a brand-new approach for the Census Bureau and is different from all prior Census Bureau initiatives in regard to disclosure avoidance. As a component of the DP initiative, the Census Bureau has released a series of "demonstration products" (Abowd, 2020, Census Bureau 2020a, 2020b, 202c, 2020d, 2020e, 2020f, and 2020g) that allow outside analysts and stakeholders to determine for their purposes the impact DP would have on Census data. These demonstration products generally contain:

- the most common, basic demographic and housing variables

- different levels of geography
- 2010 census data as they were originally reported
- 2010 census data adjusted (perturbed) by DP

As the Census Bureau responded to User complaints about poor accuracy, the "privacy budgets" were changed in the demonstration products to provide higher levels of accuracy (Beveridge, 2021). Here, we examine the errors introduced by DP on 2010 Census block data for Mississippi in the form of four case studies. In our initial analysis, we employ the "demonstration product" for census blocks in Mississippi released May 27th, 2020, file (labeled as 2020527) with an epsilon level of 4.0 , which was downloaded from the Minnesota Population Center's NHGIS site: https://nhgis.org/privacy-protected-demonstration-data. Against the results we find from the May 27th, 2020 file, we compare results from the most recent release, April 28th, 2021. (file labeled as 20210428) with an epsilon level of 10.3, which was downloaded from the same Minnesota Population Center's NHGIS site.

In the comparative analyses for case studies 1 through 3, we employed the cross-tabulation routine found in Release 12 of the NCSS Statistical System (https://www.ncss.com/software/ncss/). For case study 4, we sorted the blocks in descending order by the 2010 census total population, then used the logical "IF' function to examine differences between the 2010 census count and the DP count (match = zero; non-match =1), and summed the number of non-matches.

Results from the May 27th 2020 File

*Case 1: Children without Adults: How Did Differential Privacy turn 10 blocks into 4,912***?**

The 2010 census reported that there were 10 blocks in which one or more children (under age 18) were listed, but no adults (18 years and over). There were 371 children in these ten blocks.

Out of 171,778 blocks, it is highly believable that there are ten in which a total of 371 children reside without adults. However, DP produced 4,912 such blocks in which 27,383 children reside without adults - a highly unbelievable number

Case 2: Differential Privacy turned 8,235 Blocks with one or more people of voting age into blocks with <u>zero people of voting age</u>

Case 3: Differential Privacy turned 1,886 blocks with zero persons of voting age into blocks <u>with one or more persons of voting age</u>

Case 4: Excluding the 84,813 blocks in which both the 2010 census and the DP Adjustment shows zero population, Mississippi has 89,966 blocks where either the 2010 census or the DP adjustment show at least one person. Of these 86,966 blocks:

- *83,425 (96%) show a different total population when DP is applied.*
- *82,821 (95%) show a different number of adults (18 years and over) when DP is applied*
- *72,051 (83%) show a different number of children (under 18 years of age) when DP is applied*

Results from the April 28th 2021 File

*Case 1: Children without Adults: How Did Differential Privacy turn 10 blocks into 3,100***?**

The 2010 census reported that there were 10 blocks in which one or more children (under age 18) were listed, but no adults (18 years and over). There were 371 children in these ten blocks.

Out of 171,778 blocks, we repeat that it is highly believable that there are ten in which a total of 371 children reside without adults. However, the April 28th 2021 DP demonstration product yields produced 3.100 such blocks in which 9,418 children reside without adults - a highly unbelievable number

Case 2: Differential Privacy turned 4,907 Blocks with one or more people of voting age into blocks with <u>zero people of voting age</u>

Case 3: Differential Privacy turned 3,048 blocks with zero persons of voting age into blocks with one or more persons of voting age

Case 4: Excluding the 84,997 blocks in which both the 2010 census and the DP Adjustment shows zero population, Mississippi has 86,801 blocks where either the 2010 census or the DP adjustment show at least one person. Of these 86,966 blocks:

- *80,063 (92%) show a different total population when DP is applied.*
- *77,712 (90%) show a different number of adults (18 years and over) when DP is applied*
- *69,666 (80%) show a different number of children (under 18 years of age) when DP is applied*

Discussion and Conclusion

As far as we can tell from the information available from the Minnesota Population Center, Mississippi was not subject to higher levels of DP Disclosure Avoidance than the other states in either of the two Demonstration Product" files (2020527 and 20210428) we have analyzed. Instead, the DP levels are reported as uniform across all states at an "epsilon" level of 4.0 and 10.3, respectively, for people (https://www.nhgis.org/privacy-protected-demonstration-data#v20210428_12-2). Given this and the low numbers of people found statewide in the 2010 census and its low number of 2010 census blocks, Mississippi would appear to be a candidate for a higher level of DP Disclosure Avoidance than many other states. This makes our findings all the more worrying because they show high levels of error at the census block level even at what might be described as a low level of DP Disclosure Avoidance. Finding that in going from an epsilon of 4.0 in which DP produced 4,912 census blocks in which 27,383 children reside without adults to an epsilon of 10.3 in which DP produced 3.100 such blocks in which 9,418 children reside without adults remains very troubling, as are our other three comparisons.

As the examples show in Appendix 2, if DP is implemented at either the avoidance level found in the "Demonstration Product" files 20200527 or 20210428 for census blocks in Mississippi we examined in this study, it will affect almost all of the state's users of small area census data, from legislatures relying

on

the data to design Congressional Districts to comply with the law, to demographics vendors who supply clients with zip code level characteristics so businesses can make better decisions. Other end users such as health district administrators who need the data to track health issues such as COVID-19, and businesses that use small area data such as zip codes, blocks and block groups to improve marketing, stand to be dramatically impacted. Many government agencies also depend on accurate small area census data to make programs run efficiently and effectively and the biggest impact of DP will be in small areas. The data in small areas are typically used both directly where the small area is the unit of analysis and aggregated into higher levels of geography by these users. In the case of the latter, the errors introduced by DP tend to even out. However, in the case of the former, these users and their clients will be forced to deal with erroneous data if DP is implemented.

Because it is likely that the results we found in Mississippi will be found in other states and perhaps at even higher levels of error, our examination leads us to conclude that it is likely the errors introduced by DP of the type and at the level found in the demonstration product file we examined will render the nation’s block level data essentially unusable.

Appendix 1. What is Differential Privacy?

A statement by Ben Rossi (2016) summarizes the problem with DP in regard to small areas such as census blocks: “…[I]f a database is a representative sample of an underlying population, the goal of a privacy-preserving statistical database is to enable the user to learn properties of the population as a whole, while protecting the privacy of the individuals in the sample.” This statement reveals that the DP tradeoff is to make available properties of the population as a whole, while protecting the privacy of individuals. In the world of the Census Bureau, this tradeoff has been translated to mean that the population as a whole, is defined by a population at a level of geography beyond the block. The tradeoff means that a user cannot learn properties of the population at the block level with any degree of confidence. If DP is implemented, it will affect all of the many users of small area data, to include those described earlier, the demographics vendors who supply clients with zip code level characteristics, public health and public safety organizations, and businesses that use small area data such as zip codes, school districts, and Regional Planning Organizations. The data associated with these census stakeholders are those that represent small areas directly as well as being aggregated into other small areas and into higher levels of geography. This means that DP, a statistical adjustment, will increase the error in the small area data needed by these stakeholders.

Is DP complicated? Here is a formal Definition followed by a discussion. To start, we use definition 2.4 from Dwork and Roth (2014: 17).

Definition 2.4 (Differential Privacy). A randomized algorithm $\mathcal{M}$ with domain $\mathbb{N}^{|\mathcal{X}|}$ is (ε, δ)-differentially private if for all $\mathcal{S} \subseteq \text{Range}(\mathcal{M})$ and for all $x, y \in \mathbb{N}^{|\mathcal{X}|}$ such that $\|x - y\|_1 \leq 1$:

$$\Pr[\mathcal{M}(x) \in \mathcal{S}] \leq \exp(\varepsilon) \Pr[\mathcal{M}(y) \in \mathcal{S}] + \delta,$$

Where,
M: Randomized algorithm i.e., query (db) + noise or query (db + noise).
S: All potential output of M that could be predicted.
x: Entries in the database. (i.e., N)
y: Entries in parallel database (i.e., N-1)
ε: epsilon, The maximum distance between a query on database (x) and the same query on database (y).
δ: Delta, the probability of information accidentally being leaked.

This definition of DP is a measure of “How much privacy is afforded by a query?” This is an important point in that DP represents an offer of privacy according to a provable and quantifiable amount, sometimes referred to as the privacy-loss budget (Snoke and McKay, 2019). It is this probabilistic quantifiable feature that is DP’s major selling point because other forms of DAS (Disclosure Avoidance Systems) do not provide a formal quantification of the protection they offer. How does it do this? As this suggests, DP is not the system that creates privacy; it is the system that measures privacy using the definition just given. How does DP measure privacy?

The DP algorithm gives the comparison between running a query M on database (x) and on a parallel database (y), where the latter has one less entry than database (x). The measure by which the full database(x) and the parallel database(y) can differ is given by Epsilon (ε) and delta (δ). Specifically, DP works by tying privacy to how much the answer to a question or statistic is changed given the absence or presence of the most extreme possible person in the population. This is done within a statistical framework. An example by Snoke and McKay (2019) helps to explain this. Suppose the data we want to protect is income data, and the statistic we want answered is, "What is the median income?" The most extreme person who could possibly be in any given income data could be Jeff Bezos. If he is absent or present in the data set, the median will not change much, if at all. This means that DP can provide a more accurate answer about the median income without using much privacy-loss budget.

However, what if the question is, "What is the maximum income?" Unlike the median, the answer to this question would be likely to significantly change if Bezos is absent or present in the data set. A DP algorithm would provide a less accurate answer, or require more privacy-loss budget, to answer this query and protect the extreme case, Bezos (Snoke and McKay, 2019).

So, when Epsilon (ε) is small (as shown in Definition 2.4 above), DP asserts that for all pairs of adjacent databases x, y and all outputs M, an adversary cannot distinguish which is the true database on the basis of observing the output—the probabilities are too low. That is, if we are interested in median income, it does not matter if Jeff Bezos is in or out of the data set: For this query Epsilon (ε) should be set at a high level because for a query regarding median income there is little need to "protect" the data base. This example translates formally into something like the following. When (ε) is large DP merely says that there exists neighboring databases and an output M, for which the ratio of probabilities of observing M conditioned on the database being, respectively, x or y, is large.

However, if we interested in knowing the maximum income in the data base, it will matter if Jeff Bezos is in or out of the database. Thus, Epsilon (ε) should be set at a low value to prevent "leaking" the maximum income. However, even if Epsilon (ε) is not set low, an adversary may not have the right auxiliary information to recognize that a revealing output has occurred; or may not know enough about the database(s) to determine the value of their difference.

Thus, the DP algorithm represents a statistical adjustment in that it uses a probability framework, typically based on the Laplace probability distribution (as stated elsewhere in this report), which is used to produce the errors / noise in the data. Moreover, as noted by Ruggles et al. (2019) under DP, responses of individuals cannot be divulged even if the identity of those individuals is unknown and cannot be determined. Returning to the example of a query about maximum income, it would not matter if the identify of Bezos was not divulged; the correct answer to the question about the maximum income in a dataset would not be provided under DP.

A final important point about differential privacy is that it is applied using two different types of geography: (1) "spine" which are the core census statistical geographies such as counties, tracts, and blocks; and (2) "off-spine" which are governmental or administrative geographies such as school districts and legislative districts. The "spine" geography, particularly blocks, are important because they offer the greatest geographic granularity and are the geographies DP is actually being applied to. "Off-spine" geographies are also critically important because conceptually they could capture the best or worst pieces of statistical geography and aggregate and magnify their errors. As shown in Figure X.X (above), legislative districts, voting districts, congressional districts, places, VTDs, and ZIP codes are all "off-spine," that is, not in the hierarchy of geographic areas for which the Top Down Algorithm (TDA) maximizes accuracy and so are built up from the lower-level block groups and blocks. In our analysis, we only look at blocks, which is one of the spine geographies.

Appendix 2. Selected Examples of Small Area Census Data Users

Consumer Demographics

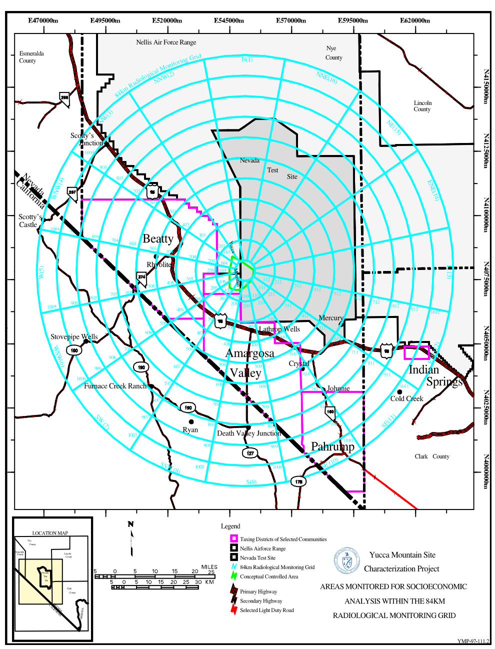
In the latter part of the 20th century, statistics became a commodity independent of government, and a statistical services industry developed (Swanson, 2013). This development is pertinent because these services are primarily a business information industry. While demographics vendors such as Claritas and ESRI generate their own zip code estimates and forecasts, the Census Bureau uses both block and block group data to generate zip code population and housing estimates (Census Bureau, 2020h). In the case of the zip code data generated by the Census Bureau, it is certain to be subject to DP if the latter is implemented; in the case of the zip code generated by demographic vendors, it is certain that the block and block group data they use in the process will be subject to DP if the latter is implemented. In 2018, for example, the Census Bureau decided to no longer approve requests for sub-state data if the data were not protected using strengthened disclosure avoidance methods providing small area data in its for-pay Custom Table operation (U.S. Census Bureau, 2020i). As an example of the importance of these data, Swanson et al. (2009) used ESRI Zip code data to assess the impacts of Hurricane Katrina in Louisiana and Mississippi.

Health and Safety

Small area data are important for public health and public safety, both for planning and reporting. As one example of the use of small area data for public health, the Mississippi State Department of Health (2016) developed an integrated HIV health care and prevention plan that uses census tract data.

As another example, the U.S. Department of Energy (1988) issued a radiological monitoring plan for the investigation of a proposed nuclear waste storage at Yucca Mountain, Nevada. The radiological studies area is defined by a circle 84 km in radius, whose center is assumed to be located at the proposed site of the central surface facilities (see Figure 1 below). The circle is divided into 160 cells radiated out from the 16 km radius area in the center of the study area, designated as the near field (NF) study area. The remainder of the area (16-84 km) is called the far field (FF) study area. The FF study area required that the population of each of the 160 cells be estimated on a regular basis, which required block, block group, and census tract data as starting points (Swanson, Carlson, and Williams, 1990). This plan would have been of use in Mississippi when nuclear bombs were detonated underground in Lamar County, one in 1964 and the other in 1966 (http://mshistorynow.mdah.state.ms.us/articles/293/nuclear-blasts-in-mississippi).

Figure 1: The Radiological Studies Area.



Natural Disaster Assessment

Closely related to public health and safety, but distinct, is natural disaster preparedness and assessment. As an example, Swanson (2008) examined the effect of Hurricane Katrina on the populations of 20 selected ZIP code areas in Mississippi and found them to be profound. In another study of the demographic effects of Hurricane Katrina, Swanson (2009) examined the effects of Hurricane Katrina on the client populations and candidates for a specific medical procedure in the service areas associated with two medical facilities on the Mississippi gulf coast. The two service areas were defined by zip codes, and in analyzing them, Swanson found that Katrina had an adverse impact on the client base of both medical facilities.

As another example, what will the Census Bureau do with its Emergency Management program (https://www.census.gov/topics/preparedness.html), which is designed to provide timely and accurate data about the effects of natural disasters? If a Category 4 hurricane strikes Hancock, Harrison, and Jackson counties, will the Census Bureau provide erroneous small area data to FEMA and local authorities?

Regional Planning Organizations

There are hundreds of regional planning organizations in the U.S. Although they exist in every state, they may come under different names in different states, (Council of Government (COG), Metropolitan Planning Organizations (MPO)) but they all have similar missions, centered on land use and transportation planning, both of which require small area data.

In conjunction with the Gulf Coast Planning Organization, the Kirwan Institute developed an index by which the geography of opportunity in the Mississippi Gulf Coast region can be viewed using census tract data (Kirwan Institute, 2012). The Central Mississippi Planning and Development District (no date) reports income data for block groups and persons per square mile by census tract. Faulty block-level data would results in the misdirection of resources intended for those populations in greatest need.

Acknowledgements

We are grateful to the Minnesota Population Center for assembling and making available the DP demonstration product file we use here.

Endnotes

1. Census blocks are statistical areas bounded by visible features such as roads, streams, and railroad tracks, and by nonvisible boundaries such as property lines, city, township, school district, county limits and short line-of-sight extensions of roads.

The building blocks for all geographic boundaries the Census Bureau tabulates data for, such as tracts, places, and American Indian Reservations.

Generally small in area. In a city, a census block looks like a city block bounded on all sides by streets. Census blocks in suburban and rural areas may be large, irregular, and bounded by a variety of features, such as roads, streams, and transmission lines. In remote areas, census blocks may encompass hundreds of square miles.

References

Abowd, J (2020). Modernizing Disclosure Avoidance: What We've Learned, Where We Are Now. https://www.census.gov/newsroom/blogs/research-matters/2020/03/modernizing_disclosu.html

Central Mississippi Planning and Development District (no date). Demographic Data (http://cmpdd.org/demographic-data/)

Dwork, C. and A. Roth. (2014). The Algorithmic Foundations of Differential Privacy. Foundations and Trends in Theoretical Computer Science 9 (3-4): 211-407 (https://www.cis.upenn.edu/~aaroth/Papers/privacybook.pdf)

Everaers, P. (2021) Editorial, Statistical Journal of the International Association of Official Statistics: Statistical Journal of the IAOS, vol. 36, no. 1, pp. 1-3, 2020 DOI-10.3233/SJI-209002.

Kirwan Institute (2012). The Geography of Opportunity in Mississippi's Gulf Coast Region. Columbus, OH. (https://grpc.com/wp-content/uploads/2018/04/FinalReport_Dec2012-2reduced.pdf).

Mississippi State Department of Health. (2016). 2017-2021 Integrated HIV Prevention and Care Plan (https://msdh.ms.gov/msdhsite/_static/resources/7022.pdf)

National Research Council (2006). Once, Only Once, and in the Right Place: Residence Rules in the Decennial Census. Panel on Residence Rules in the Decennial Census. Daniel L. Cork and Paul R. Voss, eds. Committee on National Statistics, Division of Behavioral and Social Sciences and Education. Washington, DC: The National Academies Press.

Ruggles, S., C. Fitch, D. Magnuson, and J. Schroeder. (2019). Differential Privacy: Implications for Social and Economic Research. American Economic Association Papers and Proceedings 109 (May): 403-408.

Snoke, J., and C. McKay. (2019). Differential Privacy: What is it? AMSTAT News (March). (https://magazine.amstat.org/blog/2019/03/01/differentialprivacy/).

Swanson, D.A. (2013). Consumer Demographics: Welcome to the Dark Side of Statistics. Radical Statistics 108: 38-46.

Swanson, D. A. (2009). "Hurricane Katrina: A Case Study of Its Impacts on Medical Service Providers and Their Client Populations." The Open Demography Journal 2: 8-17.

Swanson, D. A. (2008) "The Demographic Effects of Hurricane Katrina on the Mississippi Gulf Coast: An Analysis by Zip code." Journal of the Mississippi Academy of Sciences. 53 (4): 213-231.

Swanson, D., J. Carson, and C. Williams. (1990). "The Development of Small Area Socioeconomic Data to be Utilized for Impact Analysis: Rural Southern Nevada." Pp:985-990 in High Level Radioactive Waste Management: Proceedings of the 1990 International Conference, American Nuclear Society and American Society of Civil Engineers, New York, New York, 1990.

Swanson, D., R. Forgette, J. McKibben, M. Van Boening, and L. Wombold. (2009). "The Socio-Demographic and Environmental Effects of Katrina: An Impact Analysis Perspective". The Open Demography Journal. 2 (11): 36-46.

U.S. Census Bureau (no date), Title 13, U.S. Code (https://www.census.gov/history/www/reference/privacy_confidentiality/title_13_us_code.html).

U.S. Census Bureau (2012.) 2010 Census of Population and Housing, Population and Housing Unit Counts, CPH-2-26, Mississippi. U.S. Government Printing Office, Washington, DC.

U.S. Census Bureau (2018), "Disclosure Avoidance Techniques Used for the 1970 through 2010 Decennial Censuses of Population and Housing," THE RESEARCH AND METHODOLOGY DIRECTORATE, McKenna, L. U.S. Census Bureau, Washington DC., https://www.census.gov/content/dam/Census/library/working-papers/2018/adrm/Disclosure%20Avoidance%20for%20the%201970-2010%20Censuses.pdf

U.S. Census Bureau (2020a). 2020 Census Disclosure Avoidance Improvement Metrics, U.S Census Bureau, Washington DC., March 18, https://www2.census.gov/programs-surveys/decennial/2020/program-management/data-product-planning/disclosure-avoidance-system/2020-03-18-2020-census-da-improvement-metrics.pdf?#

U.S. Census Bureau (2020b). "2020 Census Data Products and the Disclosure Avoidance System, Hawes M. and Garfinkel. S. L., Planned presentation at the Census Scientific Advisory Committee meeting, March 26.

U.S. Census Bureau (2020c). DAS Updates, U.S. Census Bureau, Hawes M. June 1 Washington DC., https://www2.census.gov/programs-surveys/decennial/2020/program-management/data-product-planning/disclosure-avoidance-system/2020-06-01-das-updates.pdf?#

U.S. Census Bureau (2020d). "Disclosure Avoidance and the Census," Select Topics in International Censuses, U.S. Census Bureau, October 2020. https://www.census.gov/library/working-papers/2020/demo/disclos-avoid-census.html

U.S. Census Bureau (2020e). "Disclosure Avoidance and the 2020 Census, U.S. Census Bureau," Washington DC., Accessed November 2nd. (https://www.census.gov/about/policies/privacy/statistical_safeguards/disclosure-avoidance-2020-census.html).

U.S. Census Bureau (2020f). Error Discovered in PPM, U.S. Census Bureau, Washington DC. (https://www.census.gov/programs-surveys/decennial-census/2020-census/planning-management/2020-census-data-products/2020-das-updates.html).

U.S. Census Bureau (2020g). "2020 Disclosure Avoidance System Updates," U.S. Census Bureau, Washington DC., (https://www.census.gov/programs-surveys/decennial-census/2020-census/planning-management/2020-censusdata-products/2020-das-updates.html).

U.S. Census Bureau (2020h). Zip Code Tabulation Areas, ZCTAs (https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html).

U.S. Census Bureau (2020i). Custom Tables (https://www.census.gov/programs-surveys/acs/data/custom-tables.html).

U.S. Department of Energy (1988). NNWSI Project Environmental Field Activity Plan for Radiological Studies (https://www.nrc.gov/docs/ML0037/ML003753101.pdf).