Balancing 2020 Census Cost and Accuracy: Consequences for Congressional Apportionment and Fund Allocations

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ABSTRACT

The researchers examine how accurate the 2020 census needs to be, given that accuracy is expensive but inaccuracy distorts distributions of congressional seats and federal funds. Although the 2010 census had small measured errors for states, 0.6% on average (as measured by root-mean-square error, RMS), they project that Texas loses and Minnesota gains a seat if the 2020 census has the same errors. Projections further show that if 2020 census error for state populations increases to 0.7% RMS, an additional seat is lost by Florida and gained by Ohio, and if error increases to 1.7% RMS, Texas loses a second seat, to the benefit of Rhode Island. The researchers find expected distortions in fund allocations increase about $9–$13 billion for each 0.5% increase in average error.

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Data and software code used in the analyses are at http://bit.ly/seeskin-spencer-data.
The U.S. Constitution requires that the population be enumerated decennially, for purposes of allocating Representatives among the states.

Representatives shall be apportioned among the several States according to their respective numbers, counting the whole number of persons in each State, excluding Indians not taxed. The actual Enumeration shall be made within three Years after the first Meeting of the Congress of the United States, and within every subsequent Term of ten Years, in such Manner as they shall by Law direct. (Art. I, Sec. 2, as amended)

The Constitution requires a census but does not say how accurate the census should be. Accuracy and cost are closely related. Perfect accuracy is unattainable at any cost. As demographer Nathan Keyfitz noted, “Asking why the census cannot [accurately] count 100 percent of the population in a free society is like asking why books contain typographical errors, why manufactured products often have defects, or why the police cannot catch all criminals.” (1, 46) Accuracy can be increased through investment of more resources in the census.

Understanding the cost-accuracy tradeoff is critically important for choosing and evaluating a census design. Associated with any design is a cost-accuracy curve (“cost curve”) that specifies the cost of attaining a given profile of accuracy. The cost curve is determined by census technology and social behavior, including the cooperation of the public with providing information requested. Figure 1 shows an illustrative example of the cost curve. Empirical determination of the curve is challenging, and indeed is a reason for testing and development activities at the Census Bureau.

Our study analyzes the effects of alternative levels of 2020 census accuracy on apportionment of the House of Representatives and on allocation of billions of dollars of federal funds. We argue that paying attention to census cost alone, without concern for accuracy, leads to large and perhaps counter-intuitive shifts in allocations and apportionment.
Figure 1. The cost-accuracy curve shows the cost of attaining accuracy and the accuracy attainable at given cost. (A) Accuracy typically is attained at increasing marginal cost and (B) additional spending yields decreasing returns in accuracy.

For at least the last five censuses, high accuracy was sought and spending was adjusted to try to attain it. This is evinced by the successful requests by the Census Bureau for additional funds in the years just prior to those censuses.
By contrast, for the 2020 census, Congress adopted a cost target instead of an accuracy target, and the Census Bureau is held responsible to achieve acceptable accuracy at that cost. The target was set so that the 2020 cost per housing unit remains at the same (inflation-adjusted) level as attained in 2010, or about $12.5 billion in 2020 dollars (2, Recommendation 3). This is almost 30% below the projected cost of repeating the 2010 census methods, and is attainable only with successful innovations, notably use of internet as the main venue for census reporting, use of modern geospatial imaging to update mailing addresses, use of mobile devices by census takers to collect data from households not completing a census form, and use of administrative data to remove vacant housing units and compensate for lack of data from non-respondents. Such innovations are still under development and require testing under realistic conditions (3, 4).

The underfunding of requested census testing and development in the years leading up to the 2020 census demonstrates lack of concern for accuracy relative to cost (4, 5). Indeed, although the accuracy attainable for that cost is uncertain at this point, the concerns outside the Census Bureau have focused almost exclusively on cost (6-10). The present dominating focus on cost leaves open the possibility that the accuracy attained by the census may be unsatisfactory for society’s needs (just as a dominating focus on accuracy would run the risk of excessive spending to obtain inconsequential improvements in accuracy).

Statistical decision theory is a framework that jointly considers both costs and benefits of census accuracy and quantifies the tradeoff. This prevents excessive emphasis on either cost or accuracy. The benefits of the census arise from how its products are used. Reductions in census cost necessitate reductions in census accuracy, and reductions in accuracy lead to distortions in census uses. In certain situations, the benefit of a good can be reflected by its value in the market. However, the market does not properly value data, as data is a public good and will not be
adequately provisioned by the free market (11). The most visible uses of the census results include intergovernmental allocation of funds by formulas using population statistics, apportionment of the U.S. House of Representatives, and redrawing of Congressional district boundaries. When the census population numbers contain errors, the fund allocations, Congressional apportionment, and district sizes are different than what they would be if the census numbers had no error.

Historically, census counts understated true size of population, and census error was quantified by net undercount rate, which equals error (census minus true) divided by true. Although the estimated net undercount rate for 1990 was 1.61%, the censuses in 2000 and 2001 were estimated to exceed true population size nationally, with net undercount rates estimated at –0.49% and –0.01%, respectively (12). For census uses that involve dividing a fixed total, including apportionment of the House of Representatives (“House”) and programs that use statistical formulas to allocate fixed amounts of fund total among states, what matters are the states’ differential undercount rates, defined as the net undercount rate for the state minus the rate for all states combined. Differential net undercount rates are defined analogously for demographic groups, with estimates shown in Table 1. The differential rates are fairly consistent across the three censuses, with non-Hispanic Whites overcounted relative to the nation as a whole, and Hispanics and non-Hispanic Blacks undercounted.

Inaccuracy in the census can distort the reapportionment of the House, where states can gain or lose a seat after only small changes in population (1). The distribution of House seats depends on the states’ shares of population and is calculated by the “equal proportions” method (13-16). Projections of House reapportionment following the 2020 census can be calculated from projections of 2020 state population shares (17). To illustrate effects of census inaccuracy on apportionment, we modify the projections of 2020 state population by allowing for census errors.
Balancing 2020 Census Cost and Accuracy

<table>
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<tr>
<th>Group</th>
<th>Estimated Differential Net Undercount (%)</th>
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</thead>
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<tr>
<td></td>
<td>1990 Census</td>
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<tr>
<td>Non-Hispanic White</td>
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</tr>
<tr>
<td>Non-Hispanic Asian</td>
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</tr>
<tr>
<td>Hispanic</td>
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<tr>
<td>Non-Hispanic Black</td>
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<td>Non-Hispanic native Hawaiian or other Pacific Islander</td>
<td>0.8</td>
</tr>
<tr>
<td>American Indian on reservation</td>
<td>10.6</td>
</tr>
<tr>
<td>American Indian off reservation</td>
<td>n.a.</td>
</tr>
</tbody>
</table>

Table 1. Estimated differential net undercount rates for demographic groups in last 3 censuses. Source: (12)

Table 2 shows illustrative projections of winners and losers under three alternative levels of census error. The first column shows the effect on apportionment if errors in 2020 census state population shares equal errors measured for the 2010 census (18) – Texas loses a House seat to Minnesota. The last two columns show shifts in House seats if the patterns of error in the 2020 census resemble those measured for states in the 2010 census, but the overall error in population shares is exaggerated in 2020 due to underfunding. If the sizes of errors in 2020 are 20% larger than for 2010 (RMS size 0.70 versus 0.59), Florida also loses a seat and Ohio gains one; if the RMS sizes of the errors in 2020 is 1.66, Texas is projected to lose a second seat, to the benefit of
Rhode Island. In relying on 2010 census error estimates, these projections may be conservative due to changing demographics. For example, Hispanics comprise a larger proportion of Florida’s population now than in 2010, and Hispanics tend to be undercounted relative to non-Hispanic Whites.

<table>
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<tr>
<th>State</th>
<th>RMS$^1$ relative error in state 2020 population shares</th>
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<tr>
<td></td>
<td>0.59$^2$</td>
</tr>
<tr>
<td>Florida</td>
<td>–</td>
</tr>
<tr>
<td>Minnesota</td>
<td>gain 1</td>
</tr>
<tr>
<td>Ohio</td>
<td>–</td>
</tr>
<tr>
<td>Rhode Island</td>
<td>–</td>
</tr>
<tr>
<td>Texas</td>
<td>lose 1</td>
</tr>
<tr>
<td>Every other state</td>
<td>–</td>
</tr>
<tr>
<td>Seats shifted</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2. Projected gains and losses of House seats at different levels of 2020 census error. – indicates no change. $^1$ RMS relative error is root-mean-square relative error. $^2$ The measured errors for states the 2010 census had RMS size 0.59.
Seeskin (19) shows that the expected number of changes in House seats due to error in the 2020 census tends to increase by about 2.5 – 3.5 when the root-mean-square (RMS) size of state errors increases by 1%. The RMS size of state errors is the square root of the mean of the states’ squared undercount rates; columns 1, 2, and 3 in Table 2 correspond to 2020 census error RMS sizes of 0.59%, 0.70%, and 1.66% respectively. Seeskin considered a variety of parametric error models, including state undercount rates multivariate normally distributed with zero mean, equal variance, and constant correlation, as well as other models (20). The right-hand axis of Figure 2 shows the expected number of shifts in House seats for the models with correlation 0 and 0.5 as well as the error distributions used in Table 1, which were patterned on the measured errors for the 2010 census. When the errors are random, the actual number of malapportioned seats can be less than or appreciably greater than the expected number; e.g., in the model with uncorrelated errors, the actual number of malapportioned seats has about a 1 in 7 chance of being at least 20 with RMSE at 4%, at least 16 at 3%, and at least 10 at 2% (19, 40).
Figure 2. Expected funds misallocations and malapportioned House seats.
(FY2015 dollars)

Census data affect the distribution of many billions of dollars of funds – more than $675 billion in allocations from 132 programs in FY 2015 according to a recent Census Bureau study (19). In fact, the cost-benefit analyses that have been carried out to date have focused on uses of census data for allocation of funds (22-27). With so many programs, it is not feasible to study the effects of census error on each program, and Seeskin (19) selected a disproportionate stratified sample of 18 programs that accounted for 80% of the total obligations in FY 2007 (28). Sample weighting estimates were used to obtain unbiased estimates reflecting all allocation programs listed in both
(19) and (28), and sampling variances were relatively small (c.v. < 4%). The expected amount of misallocated funds due to census error (if the same programs are in place at the same funding level for the decade following the 2020 census) is estimated at $80 billion for the decade if the RMS size of the census errors is as large as 4%. As seen in Figure 2 (left hand axis), the expected amount misallocated increases linearly with the RMS size. Actual misallocations can be higher or lower than expected amounts.

Apportionment and allocations of funds, along with redistricting following each census, are highly visible uses of census data, but they are not the only important uses. It is noteworthy that some of the most important uses of the census may be the least visible, including research in social, economic, behavioral, medical, and policy areas and applications of that research. The role of census data in policy development and decision-making by the Congress and the White House, by state and local governments, and by businesses and other organizations has not received sufficient study. For example, surveys are widely used sources of information, and almost all national population surveys – whether government or private sector, whether by internet, mail, phone, or in-person – directly or indirectly use decennial census numbers for adjusting their results. Public health impacts of census error are discussed in (29).

In conclusion, inaccuracy in the 2020 census can cause quite large – and counterintuitive – distortions in distributions of federal funds to states and local governments. If the average root-mean-square error of state populations is 2%, the expected shifts in fund allocations is on the order of $40 – $50 billion over ten years and the expected shifts in House apportionment is around 6 seats; if the average RMS error is as large as 4%, the expected shifts double in size. The actual shifts could be smaller or even greater than the expected values. We hope the average error is much
smaller than 2% or 4%, as appears to be the case for previous censuses (30), but the reality will strongly depend on the level of census funding.

References


census.gov/coverage_measurement/pdfs/g01.pdf).


20. Technical Appendix in this document.


28. L. M. Blumerman, P. M. Vidal, P. M., Uses of population and income statistics in federal funds distribution – with a focus on Census Bureau data (Governments Division Report.


33. Census Bureau, Congressional apportionment (2010 Census Brief, 2011; [https://www.census.gov/prod/cen2010/briefs/c2010br-08.pdf](https://www.census.gov/prod/cen2010/briefs/c2010br-08.pdf)).


Technical Appendix

Introduction

The calculations of errors in apportionment and in fund allocation involve joint specification of the true population and the census population numbers for states, or equivalently the true population numbers and the census errors. This was carried out in three different ways.

i. For errors in apportionment in Table 2, we projected the true 2020 population numbers by linearly extrapolating postcensal estimates from 2017, and error models were derived by scaling the measured errors in the 2010 census (18).

ii. For errors in apportionment in Figure 2, we developed a multivariate probability distribution for the 2020 true population sizes, with mean vector equal to state population projections based on the 2010 census and constant relative variances based on empirical differences between 2010 census numbers and projections for April 1, 2010 (19). A variety of alternative parametric models were developed for 2020 census errors conditional on the true 2020 population.

iii. For errors in fund allocation in Figure 2, we used a different approach. Unlike apportionment, which depends only on state population sizes in 2020, formula-based allocations of funds depend on a wide variety of population statistics and other statistics. Rather than jointly forecast the values of all such statistics ahead to 2020, which would involve complexity and uncertainty of forecasts, we obtained the latest values available of the statistics used to calculate allocations for the 18 programs studied, and we treated those as error-free. For example, the state population numbers used in our analysis of
allocation of funds might be based on the 2010 census or on postcensal estimates, but not on projections or forecasts of the 2020 population sizes.

**Projected Gains and Losses of House Seats at Alternative Levels of Census Error in Table 2**

A projection of the state population sizes for apportionment after the 2020 census is created, and then this is adjusted for three alternative levels of 2020 census error. The projection of 2020 apportionment populations is developed in 2 steps.

i. The Census Bureau’s postcensal estimates for 7/1/2016 (say $x$) and 7/1/2017 ($y$) are linearly extrapolated (projected) forward to 4/1/2020 ($z$), as $z = y + 2.75(y - x)$, using data from (31). The Census Bureau’s methodology is described in (32).

ii. The projection of the postcensal estimate from step 1 is adjusted for differences between the census population and the apportionment population. The adjustment for state $i$ involves multiplication of the projected population $z_i$ by the ratio $r_i$ of the 2010 apportionment population (33) to the 2010 census population (34). The adjusted population size for state $i$ is $v_i = r_i z_i$. Denote the sum of $v_i$ across the 50 states by $v_+.$

The following three steps were followed to use the estimated net undercount rates for the 50 states in the 2010 census to calculate differential net undercount rates for the states. First, we calculate undercount-adjusted population sizes. Next, we use those to calculate the undercount rate for all 50 states combined. Finally, we calculate the differential net undercount rate.

i. For state $i$, denote the undercount rate by $u_i$, the census population size by $c_i$, and the true size by $t_i$. Then, by definition, $u_i = (c_i - t_i)/t_i.$ We substitute the estimated undercount rate (18) for $u_i$ and assume it applies to the apportionment population, and so we can derive
the undercount-adjusted (UC-adjusted) population size, say $a_i$, as $a_i = r_i c_i / (1 + u_i)$. Denote the sum of $a_i$ across the 50 states by $a_+$. 

ii. The net undercount rate $u_+$ for all 50 states combined is calculated as $u_+ = (v_+ - a_+) / a_+$. 

iii. The 2010 differential net undercount rate for state $i$, say $d_i$, is calculated as $d_i = u_i - u_+$. 

The adjusted population size $v_i$ for state $i$ is further adjusted for illustrative profiles of net undercount in the 2020 census. To do this, we introduce a multiplier, $\lambda$, to apply to the differential undercount as in the 2010 census. This leads to undercount adjusted population sizes $b_i$ for 2020. The formula for this is $b_i = v_i ((1 - u_+ + \lambda d_i)$. One can interpret $\lambda > 1$ as less accuracy (larger state differential undercounts) than 2010, $\lambda = 1$ as the same accuracy as 2010, and $\lambda < 1$ as more accuracy. Notice that the RMS sizes of the differential undercount also scale by $\lambda$. Choices of $\lambda$ equal to 1, 1.2, and 2.385 correspond to RMS sizes of 0.59, 0.70, and 1.66 as shown in Table 1. Finally, the apportionments are then calculated using the Equal Proportions apportionment method with the $b_i$ values as the population sizes of the states. For $1 < \lambda < 1.2$ there were 2 House seats misallocated, for $1.2 \leq \lambda < 2.385$ there were 4 seats misallocated, and for $\lambda = 2.385$ there were 6 seats misallocated. The input data and results are available in (S2).

**Parametric Models for Census Error**

A variety of parametric error models were examined to explore the sensitivity of findings to alternative error distributions. Two of these were used to construct Figure 2. In the “base case,” which is the model underlying the “uncorrelated errors” curve in Figure 2, relative errors were independent normally distributed with zero mean and common standard deviation. The “correlated errors” case is like the base case except the errors for states have common correlation of 0.5, and it is also plotted in Figure 2. The “differential bias” case is like the base model except
that biases are present, with one sign for the 25 most populous states ("large states"), and opposite sign for all others including Washington, D.C. ("small states"), and equal magnitudes of relative biases for all states; relative standard deviations of errors for all states were equal to each other and to the absolute value of the relative biases. The "accurate small states" case is like the base case except that errors for small states were identically zero (zero means and standard deviations). For each of these models, specification of the average root-mean-square-error (RMSE) was sufficient to completely specify the model.

**Probability Distribution for 2020 Population as Used for Apportionment in Figure 2**

The joint distribution of estimates and true values of population was obtained from the conditional distribution of relative errors given the true values, as just described, and the distribution of true values, which we now describe. The distribution of true values is specified differently for analysis of apportionment, which depends only on population numbers, and analysis of fund allocations, which depend on a variety of statistics in addition to population.

For apportionment, true population sizes were taken to be multivariate normal with means equal to projections for 2020, prepared by the University of Virginia’s Weldon Cooper Center for Public Service based on the 2010 census results, (35) and covariance matrix consistent with empirical errors in past ten-year projections for 2010 (19, 179-181). Apportionments are integers, and it is theoretically possible that a change in population of 1 person can cause a state to gain or lose a seat (1). Specifying a variance for the true values prevents our estimates from being sensitive to true population sizes being necessarily near or far from values that would change apportionments. Simulations showed the variance around the means to have little if any effect on the estimates of malapportionment arising from census inaccuracy.
Expected Shifts of House Seats in *Figure 2* with Alternative Models of Census Error

A simulation was conducted in which population vectors were randomly drawn from the multivariate normal distribution described in the preceding paragraph, and relative errors were randomly selected from the error models and from an assumption of zero error (corresponding to correct apportionment for the population vector selected). House apportionments were calculated according to the equal proportions method. Standard errors for all estimates are less than 0.05 House seats (19, 37). The curves relating to the right-hand axis in *Figure 2* are taken from Figure 2.1 in (19, 25). Table 2.5 in (19, 39) describes the probability distribution of the number of House seats misallocated under the “uncorrelated errors” or “base case” error model. Table 2.9 in (19, 45) provides a fitted linear regression of malapportioned House seats as a function of parameters specifying the multivariate distribution of state census numbers.

Expected Sum of Misallocated Funds with Alternative Models of Census Error in *Figure 2*

A stratified simple random sample of 18 formula-based fund allocation programs was selected from the 140 listed in (28) as using Census Bureau population or income data to determine the allocations (19, 168-170). We selected with certainty the 8 largest programs, which accounted for 4/5 of the total FY 2007 obligations, and a disproportionate stratified sample of 10 of the remaining 132 programs. These are shown in Table A.3. Sample weights equal to the reciprocal of the sampling probability were constructed; the probability was equal to \( n_h/N_h \) with \( n_h \) the sample size and \( N_h \) the population size in stratum \( h \). For each selected program, we identified the effect of census error on allocations (19, 31-37). For any given parametric model of census error, the expected value of the sum of misallocations for the selected program was estimated via simulation. This was converted to a proportion of the total amount allocated for the year for which the data
were available (19, 42, 45), and then the proportion was multiplied by the FY2015 obligation from (19). The weighted sum of the latter estimated expected values was calculated, using weights equal to the ratio of the number of programs in the stratum divided by the sampled number of programs in the stratum. The weighted sum estimates the sum of the expected values of misallocations for all 140 allocation programs in (28) if their allocated amounts were equal to the FY2015 obligations in (19). However, the population sampled excludes 7 programs that came into being between FY2007 and FY2015, and whose FY2015 obligations totaled $93.9 billion, and includes 15 FY2007 programs that did not exist in FY2015, totaling $2.3 billion in 2015 dollars (19). (FY2007 dollars were converted to FY2015 dollars according to the Consumer Price Index for Urban Wage Earners and Clerical Workers (36), yielding an adjustment factor of 231.810/202.767 = 1.143.) Sampling errors (reflecting finite number of simulations as well as sampling of the allocation programs) for FY2009 amounts were moderate, with margins of error (two standard errors) of about 15% of the total being estimated (19, 27).

Data used in the computations, if not provided above, may be found at http://bit.ly/seeskin-spencer-data.
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<th>Stratum</th>
<th>( n_h / N_h )</th>
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*Table A.3. Sampled programs allocating federal funds.* Source: columns 2 – 4 from (27) and columns 5 – 6 from (21).