
From: Kathleen M Styles (CENSUS/ADDC FED) [kathleen.m.styles@census.gov]
Sent: 9/11/2020 1:23:10 PM
To: John Maron Abowd (CENSUS/ADRM FED) [john.maron.abowd@census.gov]
Subject: Fw: Activity in Case 8:19-cv-02710-PX-PAH-ELH La Union Del Pueblo Entero et al v. Trump et al Notice (Other)
Attachments: Comments on LUPE II Declarations.docx; 112.7 - Ex F - Decl. of Andrew Reamer.pdf; 112.6 - Ex. E -Decl. of Kimball Brace.pdf; 112.5 - Ex. D- Decl. of Amy O'Hara.pdf; 112.4 - Ex. C - Decl. of Dr. William O'HAre.pdf; 112.3 - Ex. B Expert Decl of Howard Hogan.pdf; 112.2 -Ex. A Expert Decl. of John thompson.pdf

Kathleen M. Styles
Chief, Decennial Communications and Stakeholder Relationships
U.S. Bureau of the Census

(b)(6)
(301) 763-0235 Office
(b)(6) Cell

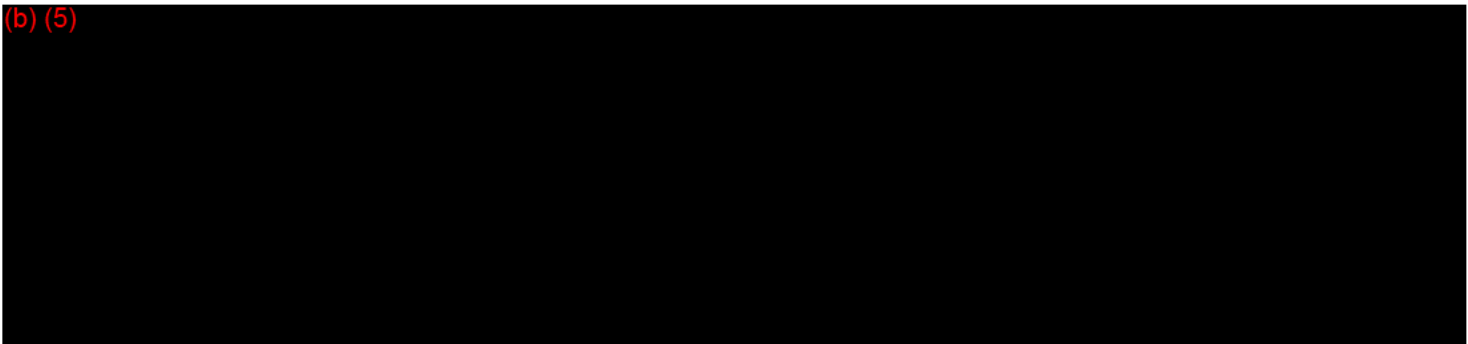
From: Enrique Lamas (CENSUS/DEPDIR FED) <Enrique.Lamas@census.gov>
Sent: Sunday, September 6, 2020 5:01 PM
To: Kathleen M Styles (CENSUS/ADDC FED) <kathleen.m.styles@census.gov>
Cc: Albert E Fontenot (CENSUS/ADDC FED) <Albert.E.Fontenot@census.gov>; Christa D Jones (CENSUS/DEPDIR FED) <Christa.D.Jones@census.gov>; John Maron Abowd (CENSUS/ADRM FED) <john.maron.abowd@census.gov>
Subject: Re: Activity in Case 8:19-cv-02710-PX-PAH-ELH La Union Del Pueblo Entero et al v. Trump et al Notice (Other)

I agree with Kathleen. The declarations are not unreasonable and we don't need to refute smaller disagreements. On the issue of internal knowledge by Amy O'Hara, Mike Cannon asked Christa and me last week and we said it was not likely. Many academics know admin records outside the bureau and past directors often provide opinions on census matters. So I do not see where Amy used internal information.

Enrique Lamas
Senior Advisor
Director's Office
U.S. Census Bureau
Office: 301-763-3811

On Sep 6, 2020, at 4:00 PM, Kathleen M Styles (CENSUS/ADDC FED) <kathleen.m.styles@census.gov> wrote:

(b) (5)



Kathleen M. Styles

Chief, Decennial Communications and Stakeholder Relationships

U.S. Bureau of the Census

(b)(6)

(301) 763-0235 Office

(b)(6) Cell

From: Ehrlich, Stephen (CIV) <Stephen.Ehrlich@usdoj.gov>

Sent: Saturday, September 5, 2020 3:30 AM

To: Albert E Fontenot (CENSUS/ADDC FED) <Albert.E.Fontenot@census.gov>; Kathleen M Styles (CENSUS/ADDC FED) <kathleen.m.styles@census.gov>; Christa D Jones (CENSUS/DEPDIR FED) <Christa.D.Jones@census.gov>; Enrique Lamas (CENSUS/DEPDIR FED) <Enrique.Lamas@census.gov>; John Maron Abowd (CENSUS/ADRM FED) <john.maron.abowd@census.gov>; Cannon, Michael <MCannon@doc.gov>; DiGiacomo, Brian <bDiGiacco@doc.gov>; Heller, Megan <MHeller@doc.gov>; Kourkoumelis, Aristidis <AKourkoumelis@doc.gov>; Sharma, Sapna <SSharma@doc.gov>

Cc: Kelleher, Diane (CIV) <Diane.Kelleher@usdoj.gov>; Sverdlov, Alexander V. <Alexander.V.Sverdlov@usdoj.gov>; Zee, M. Andrew (CIV) <M.Andrew.Zee@usdoj.gov>

Subject: FW: Activity in Case 8:19-cv-02710-PX-PAH-ELH La Union Del Pueblo Entero et al v. Trump et al Notice (Other)

(b) (5)



Stephen Ehrlich

Trial Attorney

U.S. Department of Justice

Civil Division | Federal Programs Branch

202-305-9803 | stephen.ehrlich@usdoj.gov

From: MDD_CM-ECF_Filing@mdd.uscourts.gov <MDD_CM-ECF_Filing@mdd.uscourts.gov>

Sent: Friday, September 04, 2020 11:39 PM

To: MDDdb_ECF@mdd.uscourts.gov

Subject: Activity in Case 8:19-cv-02710-PX-PAH-ELH La Union Del Pueblo Entero et al v. Trump et al Notice (Other)

BC-DOC-CEN-2020-001602-001005

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**U.S. District Court
District of Maryland**

Notice of Electronic Filing

The following transaction was entered by Minnis, Terry on 9/4/2020 at 11:38 PM EDT and filed on 9/4/2020

Case Name: La Union Del Pueblo Entero et al v. Trump et al
Case Number: 8:19-cv-02710-PX-PAH-ELH
Filer: Marco Abarca
Lydia Camarillo
Ralph Carmona
Deborah Chen
David Chiu
Cynthia Choi
Kenny Chu
Coalition for Humane Immigrant Rights of Los Angeles
Felipe Cruz
Javier Gaston-Greenberg
Rogene Gee Calvert
Mia Gregerson
Candy L. Gutierrez
Zeenat Nisha Hasan
Jeffrey D. Hsi
La Union Del Pueblo Entero
Maricela Lechuga
Raj Mukherji
Albert Muratsuchi
Organization of Chinese Americans-Greater Houston
Alexandra Rosy Palomo-Pujol
Vincent Pan
John Park
Promise Arizona
Marty Ramirez
Jennifer Reyes
Raymond Sanchez
Phillip Ting
Jacinta Titilii Abott
Sharon Tomiko Santos
Juanita Valdez-Cox
Eugene Wu

Docket Text:

NOTICE by Marco Abarca, Lydia Camarillo, Ralph Carmona, Deborah Chen, David Chiu, Cynthia Choi, Kenny Chu, Coalition for Humane Immigrant Rights of Los Angeles, Felipe Cruz, Javier Gaston-Greenberg, Rogene Gee Calvert, Mia Gregerson, Candy L. Gutierrez, Zeenat Nisha Hasan, Jeffrey D. Hsi, La Union Del Pueblo Entero, Maricela Lechuga, Raj Mukherji, Albert Muratsuchi, Organization of Chinese Americans-Greater Houston, Alexandra Rosy Palomo-Pujol, Vincent Pan, John Park, Promise Arizona, Marty Ramirez, Jennifer Reyes, Raymond Sanchez, Phillip Ting, Jacinta Titalii Abott, Sharon Tomiko Santos, Juanita Valdez-Cox, Eugene Wu, Yicheng Wu re [112] Emergency MOTION for Temporary Restraining Order *and/or Preliminary Injunction* (Attachments: # (1) Exhibit A, # (2) Exhibit B, # (3) Exhibit C, # (4) Exhibit D)(Minnis, Terry)

8:19-cv-02710-PX-PAH-ELH Notice has been electronically mailed to:

Alan E Schoenfeld alan.schoenfeld@wilmerhale.com

Andrea E Senteno asenteno@maldef.org

Daniel A Hatoum dhatoum@maldef.org

Daniel T Donovan ddonovan@kirkland.com

Debo P Adegbile debo.adegbile@wilmerhale.com

Eri Andriola eandriola@advancingjustice-aajc.org

Gregory George Schwab gschwab@pa.gov

Jamie Dycus jamie.dycus@wilmerhale.com

Nina Perales nperales@maldef.org, cleija@maldef.org, ipina@maldef.org

Niyati Shah nshah@advancingjustice-aajc.org

Patrick Brown patrick.brown@kirkland.com

Stephen Ehrlich stephen.ehrlich@usdoj.gov, tracey.l.urban@usdoj.gov

Susan M Davies susan.davies@kirkland.com

Tanya G Pellegrini tpellegrini@maldef.org

Terry Ao Minnis tminnis@advancingjustice-aajc.org

Thomas Saenz tsaenz@maldef.org

W. Neil Eggleston Neil.Eggleston@kirkland.com

8:19-cv-02710-PX-PAH-ELH Notice will not be electronically delivered to:

The following document(s) are associated with this transaction:

Document description:Main Document

Original filename:n/a

Electronic document Stamp:

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7035eb987edbd7cce1dd5a4f2948fda6cec75b5045809014aa1276787d16]]

Document description:Exhibit A

Original filename:n/a

Electronic document Stamp:

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Document description:Exhibit B

Original filename:n/a

Electronic document Stamp:

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f9a6514790da05938584d19db9e6c9202846d9039286f1c4057eb2db42ce]]

Document description:Exhibit C

Original filename:n/a

Electronic document Stamp:

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Document description:Exhibit D

Original filename:n/a

Electronic document Stamp:

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<Comments on LUPE II Declarations.docx>

<Abowd Declaration + FINAL + legal.pdf>

(b) (5)



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EXHIBIT F

**UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF MARYLAND**

LA UNIÓN DEL PUEBLO ENTERO, et al.,

Plaintiffs,

v.

DONALD J. TRUMP, sued in his official
capacity as President of the United States, et
al.,

Defendants.

Civil Action No. 8:19-CV-02710-PX

DECLARATION OF DR. ANDREW REAMER

I. Introduction

1. I have been retained by the Plaintiffs in *La Union del Pueblo Entero, et al. v. Trump, et al.*, (regarding Civil Action No. 8:19-CV-02710-PX in the District Court of Maryland) to prepare a report on the portion of federal funds that are distributed based on data derived from the decennial Census and the effect of a differential undercount in the decennial Census on the distribution of federal funding to states and localities.

II. Qualifications

2. I am a research professor in the George Washington Institute of Public Policy (GWIPP) at the George Washington University in Washington, D.C. GWIPP research faculty focus on various aspects of the public policies of the federal, state, and local governments. GWIPP research is funded through grants and contracts from the federal government, philanthropies, and nonprofit research organizations.

3. My research aims to support U.S. national economic development and competitiveness. A substantial component of my work concerns the roles and functioning of the federal statistical system.

4. I am a member of two federal statistical advisory committees—the U.S. Bureau of Economic Analysis (BEA) Advisory Committee and the Workforce Information Advisory Council. I provide staff support to the Committee on Economic Statistics of the American Economic Association. I also am a member of the Statistics Committee of the National Association for Business Economics (NABE). The NABE Statistics Committee meets three times yearly with the directors of the U.S. Census Bureau, the U.S. Bureau of Labor Statistics, and BEA.

5. I am a board member of the Industry Studies Association and am organizing a webinar series on federal industrial policy. I am an active member and former president and former board member of the Association of Public Data Users.

6. I began my research at GWIPP in 2011, after six years at the Brookings Institution's Metropolitan Policy Program and 20 years as a consultant in U.S. regional economic development and public policy.

7. At GWIPP and Brookings, I have been responsible for encouraging a strong, well-functioning federal statistical system that met the data needs of public and private stakeholders. To that end, I have been instrumental in ensuring the continued existence of three Census Bureau programs – the American Community Survey (ACS) in 2005, 2012, and 2015; the Survey of Business Owners (SBO) in 2007; and the Longitudinal Employer-Household Dynamics (LEHD) Program in 2008.

8. As an economic development consultant, I prepared strategic analyses and plans that relied heavily on federal demographic and economic statistics. For the U.S. Economic Development Administration, I co-authored “Socioeconomic data for understanding your regional economy: a user's guide” (1998).

9. I received a Ph.D. in Economic Development and Public Policy and a Master of City Planning from the Massachusetts Institute of Technology and a Bachelor of Science in Economics from the Wharton School, University of Pennsylvania.

10. I recently conducted the research project “*Counting for Dollars 2020: The Role of the Decennial Census in the Geographic Distribution of Federal Funds.*” Project reports published include:¹

- Report #1: Initial Analysis: 16 Large Census-guided Financial Assistance Programs (August 2017)
- Report #2: Estimating Fiscal Costs of a Census Undercount to States (March 2018)
- Report #3: Federal Funding for Rural America: The Role of the Decennial Census (December 2018)
- Report #4: Census-derived Datasets Used to Distribute Federal Funds (December 2018)
- Report #5: Distribution of Funding from 55 Large Census-guided Programs by State (May 2019)
- Report #6: The Distribution of Census-Guided Federal Funds to U.S. Communities: Five Program Examples (July 2019)

¹ All reports are available at <https://gwipp.gwu.edu/counting-dollars-2020-role-decennial-census-geographic-distribution-federal-funds>.

- Report #7: Comprehensive Accounting of Census-Guided Federal Spending (FY2017)
 - Part A: Nationwide Analysis (November 2019)
 - Part B: State Estimates (February 2020)

11. At the Brookings Institution, I conceived of and carried out a Counting for Dollars 2010 study that identified census-guided federal financial assistance programs and calculated FY2008 funding flows by program to states, metro areas, and counties, although with a substantially smaller level of effort than my current project.² A full resume and list of publications is attached as an exhibit to this report. I am being paid at a rate of \$300 per hour.

III. Summary of Opinions

12. Those states, counties, and communities with an undercount of formula-relevant populations greater than that for the U.S. as a whole will lose a share of funding. Those states, counties, and communities with an undercount of formula-relevant populations less than that for the U.S. as a whole will gain a share of funding.

13. Based on my experience and knowledge, when a state, county, or community loses population share due to a differential undercount, it receives less federal funding and its residents experience less access to valued programs and services than they otherwise would have received and/or the community and residents face higher taxes.

IV. Background: Federal Spending Programs Guided by Data Derived from the Decennial Census

² Andrew Reamer and Rachel Carpenter, “Counting for Dollars: The Role of the Decennial Census in the Distribution of Federal Funds,” The Brookings Institution, March 9, 2010. Available at <https://www.brookings.edu/research/counting-for-dollars-the-role-of-the-decennial-census-in-the-distribution-of-federal-funds/>.

14. A significant portion of federal spending is directed on the basis of statistics derived from the decennial census. I have identified 316 census-guided federal spending programs that geographically distributed over \$1.5 trillion in FY2017.

15. The two primary uses of census-derived data to determine the geographic distribution of federal spending are (1) setting numerical eligibility criteria and (2) numerical formulas for the geographic allocation of funds. Geographic allocation formulas based on population shares are particularly sensitive to inaccuracies in decennial data.

A. Domestic Financial Assistance

16. The federal government relies on data derived from the decennial census to geographically allocate spending through three types of programs – domestic financial assistance, tax credits, and procurement. Each of these types is reviewed below.

17. As of October 2019, U.S. federal departments and agencies offered 2,293 total domestic financial assistance programs.³ “Domestic assistance programs” provide either financial assistance (such as direct payments to individuals, grants, loans, and loan guarantees) and non-financial assistance (such as counseling) to non-federal entities within the U.S.—such as individuals, state and local governments, companies and nonprofits—to fulfill a public purpose. Federal domestic assistance is provided in every realm of domestic policy. Examples include health care, education, economic development, transportation, social services, science, technology, criminal justice, and emergency management. Domestic assistance programs do not include foreign aid.

³ “Catalog Of Federal Domestic Assistance– CFDA,” Investopedia, available at <https://www.investopedia.com/terms/c/catalog-of-federal-domestic-assistance-cfda.asp>.

18. The *Catalog of Federal Domestic Assistance* (CFDA) is the federal government's compendium of all domestic assistance programs. The CFDA categorizes each program by type (across 15 categories) and gives it a five-digit CFDA number (such as 10.500) – the first two digits identify the sponsoring department or independent agency and the last three digits designate the individual program.⁴

19. Of the 15 categories of domestic assistance, six provide direct financial assistance (see box below). Two are in the form of grants, two are in the form of direct payments, one covers direct loans, and one covers guaranteed/insured loans.

Categories of Direct Federal Domestic Financial Assistance⁵

A. Formula Grants - Allocations of money to States or their subdivisions in accordance with distribution formulas prescribed by law or administrative regulation, for activities of a continuing nature not confined to a specific project.

B. Project Grants - The funding, for fixed or known periods, of specific projects. Project grants can include fellowships, scholarships, research grants, training grants, traineeships, experimental and demonstration grants, evaluation grants, planning grants, technical assistance grants, survey grants, and construction grants.

C. Direct Payments for Specified Use - Financial assistance from the Federal government provided directly to individuals, private firms, and other private institutions to encourage or subsidize a particular activity by conditioning the receipt of the assistance on a particular performance by the recipient. This does not include solicited contracts for the procurement of goods and services for the Federal government.

D. Direct Payments with Unrestricted Use - Financial assistance from the Federal government provided directly to beneficiaries who satisfy Federal eligibility requirements

⁴ The CFDA states:

"Assistance" or "benefits" refers to the transfer of money, property, services, or anything of value, the principal purpose of which is to accomplish a public purpose of support or stimulation authorized by Federal statute. Assistance includes, but is not limited to grants, loans, loan guarantees, scholarships, mortgage loans, insurance, and other types of financial assistance, including cooperative agreements; property, technical assistance, counseling, statistical, and other expert information; and service activities of regulatory agencies. It does not include the provision of conventional public information services. (U.S. General Services Administration, *2019 Catalog of Federal Domestic Assistance*, October 2019, p. 1)

Until recently, the CFDA was available at www.cfda.gov. The information has been transferred to a new searchable website, <https://beta.sam.gov/>.

⁵ *Ibid.*, pp. 1-2. The CFDA identifies each assistance category with a capital letter (A through O).

with no restrictions being imposed on the recipient as to how the money is spent. Included are payments under retirement, pension, and compensatory programs.

E. Direct Loans - Financial assistance provided through the lending of Federal monies for a specific period of time, with a reasonable expectation of repayment. Such loans may or may not require the payment of interest.

F. Guaranteed/Insured Loans - Programs in which the Federal government makes an arrangement to indemnify a lender against part or all of any defaults by those responsible for repayment of loans.^{6,7}

20. In Fiscal Year (FY) 2019, the federal government provided \$3,938,931,000,000 in direct domestic financial assistance programs across the above six categories, an amount equal to 18.6 percent of Gross Domestic Product (GDP) over the same period.

- Of that total, \$2,561,537,000,000 were **direct payments** to individuals and \$721,140,000,000 were **grants**, primarily to state and local governments.⁸
- In addition, in FY2019 the federal government made commitments for **guaranteed loans** totaling \$482,685,000,000 and **direct loan** obligations of \$173,569,000,000.⁹

| Federal Domestic Assistance by Category, FY2019 | |
|---|---------------------|
| Direct Payments to Individuals | \$2,561,537,000,000 |
| Grants | \$721,140,000,000 |
| Guaranteed Loans | \$482,685,000,000 |

⁶ Recipients of federal direct and guaranteed/insured loans include, for example, students, homeowners, small businesses, and farmers.

⁷ Insurance is an additional category of financial assistance, although one that does not result in an immediate financial transfer. This category includes such programs as bank deposit insurance, pension guarantees, disaster insurance (flood, crop), and terrorism and other security-related risks. The CFDA defines the Insurance category as “Financial assistance provided to assure reimbursement for losses sustained under specified conditions. Coverage may be provided directly by the Federal government or through private carriers and may or may not involve the payment of premiums.” I have not found a census-guided federal insurance program and so that category is not part of this analysis.

⁸ Figures from Historical Table 6.1 - Composition of Outlays: 1940–2025 of “Budget of the United States Government, Fiscal Year 2021,” February 2020, available at https://www.whitehouse.gov/wp-content/uploads/2020/02/hist06z1_fy21.xlsx.

⁹ Office of Management and Budget, “Analytical Perspectives, Budget of the United States Government, Fiscal Year 2019,” Supplemental Materials, February 2018, Table 19.8: Direct Loan Transactions of the Federal Government and Table 19.9: Guaranteed Loan Transactions of the Federal Government, available at <https://www.whitehouse.gov/omb/analytical-perspectives/>.

| | |
|-------------------------|----------------------------|
| Direct Loan Obligations | \$173,569,000,000 |
| Total | \$3,938,931,000,000 |

B. Tax Credits

21. Distinct from the distribution of federal funds through financial assistance programs, tax credits reduce federal revenues. In legal terms, tax credits are known as “tax expenditures.”

22. Tax expenditures are defined under the Congressional Budget and Impoundment Control Act of 1974 (the “Budget Act”) as “revenue losses attributable to provisions of the Federal tax laws which allow a special exclusion, exemption, or deduction from gross income or which provide a special credit, a preferential rate of tax, or a deferral of tax liability.” Thus, tax expenditures include any reductions in income tax liabilities that result from special tax provisions or regulations that provide tax benefits to particular taxpayers.

23. Special income tax provisions are referred to as tax expenditures because they may be analogous to direct outlay programs and may be considered alternative means of accomplishing similar budget policy objectives. Tax expenditures are similar to direct spending programs that function as entitlements to those who meet the established statutory criteria.¹⁰

24. The federal budget for FY2021 lists 165 provisions for federal income tax expenditures, covering returns from both individuals and corporations. Estimated expenditures by provision are provided, but not a total across all 165.¹¹

C. Federal Procurement

¹⁰ Joint Committee on Taxation, “Estimates of Federal Tax Expenditures for Fiscal Years 2017-2021,” JCX-34-18, May 25, 2018, p. 2.

¹¹ Office of Management and Budget, “Chapter 13, Tax Expenditures, Analytical Perspectives volume of the Budget of the United States Government, Fiscal Year 2021” February 2020, available at https://www.whitehouse.gov/wp-content/uploads/2020/02/ap_13_expenditures_fy21.pdf.

25. In FY2019, the federal government spent \$586.2 billion on the procurement of goods and services. Of this amount, \$381.2 billion was for the Department of Defense and \$205.1 billion for civilian agencies. Top-spending civilian agencies were the Department of Energy (\$33.3 billion), Department of Veterans Affairs (\$27.3 billion), Department of Health and Human Services (\$26.5 billion), and NASA (\$18.2 billion).¹²

The Role of Census-derived Datasets in Guiding the Distribution of Federal Spending

26. Article 1, Section 2 of the Constitution mandates a Decennial Census for the purposes of apportioning seats in the House of Representatives. In January 1790, Congress passed the Census Act of 1790 with an amendment proposed by Representative James Madison to add questions on population characteristics beyond those needed for apportionment (that is, race, gender, and age) so that Congress might “adapt the public measures to the particular circumstances of the community.” Ever since, the Decennial Census has carried questions beyond those required for apportionment.¹³

27. For 230 years, Congress has used data derived from the Decennial Census to guide the design and implementation of public policies and programs. Over time, moreover, the size and complexity of the Decennial Census has regularly catalyzed significant advances in the statistical and survey sciences.

28. As directed or authorized by Congress, a substantial portion of federal spending is geographically allocated to state and local governments, households, businesses, and nonprofit

¹² “A Snapshot of Government-wide Contracting for FY 2019,” WatchBlog, U.S. Government Accountability Office, May 26, 2020, available at <https://blog.gao.gov/2020/05/26/a-snapshot-of-government-wide-contracting-for-fy-2019-infographic/>.

¹³ Up through 1930, every household was required to answer each Decennial Census question. Sampling began in 1940. In 1960, most census questions were placed on the “long form” that went to a sample of households. In 2005, the “long form” questions were shifted to the new American Community Survey, which had been in development for about a decade.

organizations based on statistics derived from the Decennial Census. Congress recognizes that the appropriate and equitable distribution of certain forms of spending should be guided by socioeconomic data at various levels of geography.

29. As the Decennial Census is carried out once a decade and collects data on a small number of demographic characteristics (such as household size and relationships, housing tenure, sex, age, race, ethnicity), Congress also recognizes that the decennial numbers, on their own, are not appropriate to guide the appropriate, equitable distribution of federal spending. As a result, Congress has authorized a series of more current and broadly descriptive datasets derived from the Decennial Census (made possible by the scientific advances noted above).

30. I refer to these as “census-derived datasets.” **I have identified 316 federal spending programs that rely on census-derived data. These programs distributed \$1.504 trillion in FY2017**, a figure equal to 7.8 percent of GDP.¹⁴

31. With the development of these new datasets over the course of the last century and with the extraordinary expansion of federal financial assistance in the last six decades, Congress has specified or authorized these new datasets be used to guide the appropriate, fair geographic distribution of federal funds.

32. The following box outlines the distribution of spending for 316 census-guided programs by program type, geographic level, data use, program size, and other characteristics.

| Characteristics of 316 Federal Census-Guided Spending Programs, FY2017 |
|---|
| <i>Program Type</i> |

¹⁴ Andrew Reamer, “Brief 7: Comprehensive Accounting of Census-Guided Federal Spending (FY2017), Part A: Nationwide Analysis,” Counting for Dollars 2020: The Role of the Decennial Census in the Geographic Distribution of Federal Funds, George Washington Institute of Public Policy, George Washington University, November 2019.

- **Financial assistance programs** that provide direct payments, grants, loans, and loan guarantees to state and local governments, nonprofits, businesses, and households (305 programs, \$1,465.2 billion)¹⁵
- **Matching payments** from states to the federal government required by financial assistance programs (3 programs, \$16.5 billion)
- **Tax credit programs** that allow a special exclusion, exemption, or deduction from gross income (7 programs, \$14.9 billion)
- **Procurement programs** that award federal contract dollars to small businesses located in areas selected using census-derived data (1 program, \$7.5 billion)

Geographic Level of Data

- **Local only** – 176 programs rely only on local-level census-derived data (\$970.3 billion).
- **State only** – 101 programs rely only on state-level census-derived data (\$458.9 billion).
- **State and local** – 39 programs rely on both state and local-level census-derived data (\$75.0 billion).

Data Use

- **Allocation** – Almost all programs use census-derived data to determine the amount of spending or services provided to each eligible geographic area and household (297 programs, \$1,414.8 billion).
- **Eligibility** – Forty percent of the programs use census-derived data to determine the geographic areas and households eligible to receive the program’s funding (128 programs, \$206.3 billion).
 - Most of these programs also use census-derived data to determine allocations (109 programs, \$116.9 billion).
 - Nineteen programs (\$89.4 billion) only use census-derived data for program eligibility purposes.

Allocation Variables

- **Total population** (90 programs, \$520.3 billion)
 - Per capita income – total income (from tax and other records) divided by total population (11 programs, \$410.8 billion)
 - Count of residents (79 programs, \$109.5 billion)
- **Population subsets** (226 programs, \$216.9 billion) – examples:
 - Persons in rural areas
 - Persons below 125% of federal poverty level
 - Persons age 60+ at or below 185 percent of federal poverty level
 - Persons in overcrowded housing
 - Persons unemployed
 - Children ages 5-17 below federal poverty level
 - Children under age 3
- **Categories of geographic areas** (87 programs, \$773.8 billion)
 - Examples of categories

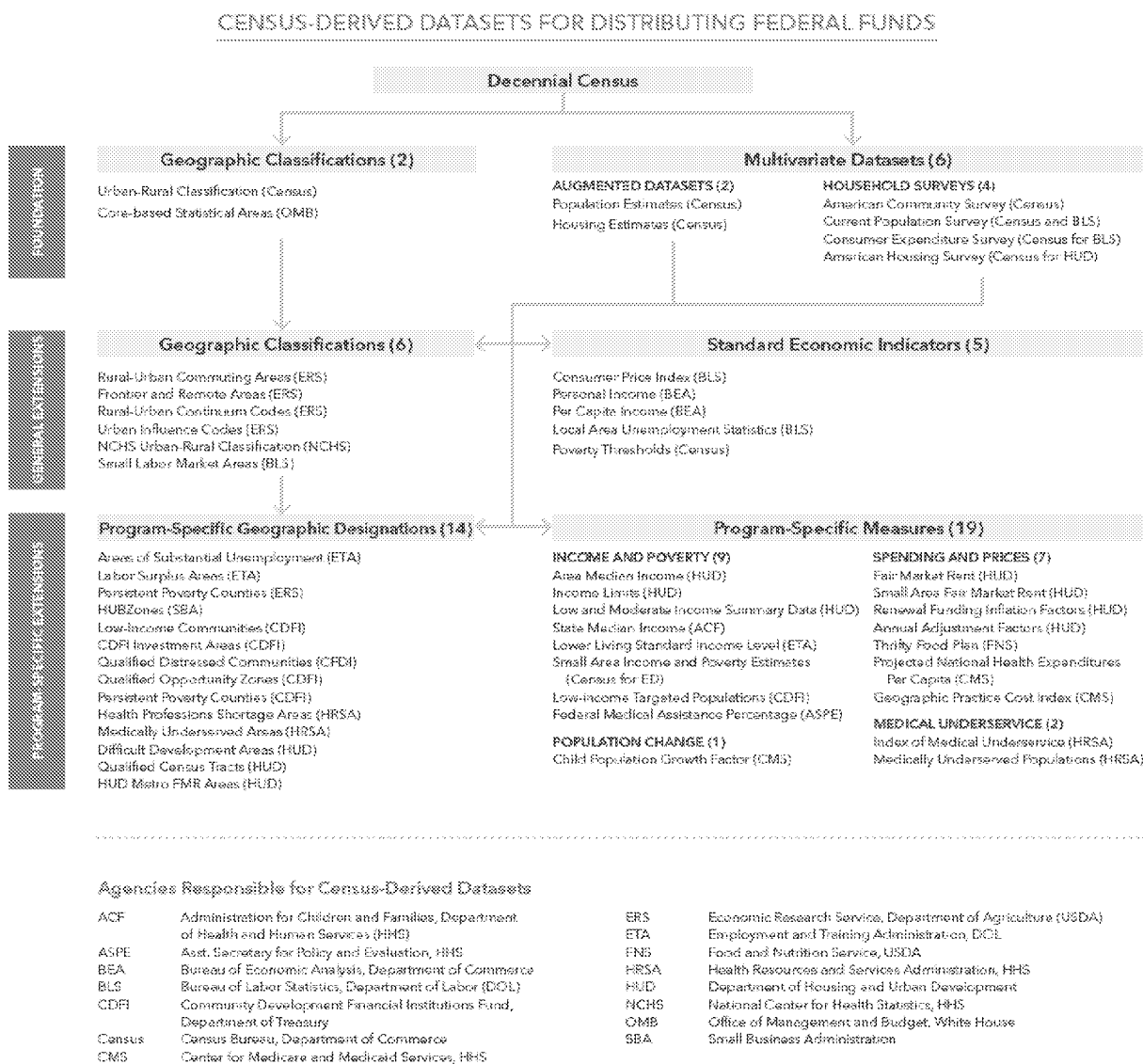
¹⁵ This figure equals 39.1 percent of all federal domestic assistance in FY2017 (\$3,745.0 billion). See footnote 8 for source.

- Large metro, metro, micro, rural, and isolated counties
- Urban, suburban, rural zip codes
- Persistent poverty counties
- Area median income as percent of state median income
- Examples of uses
 - Funds sub-allocated by category
 - Minimum percent allocation reserved for particular category
 - In competitive grant selections, points awarded vary by category
 - In competitive grant selections, preference given to one category
 - Provider service requirements vary by category

Eligibility Variables

- Geographic areas (92 programs, \$139.3 billion) – examples:
 - Population density (such as rural or urban designation)
 - Population size (above or below a specified level)
 - Unemployment rate (above a specified level)
 - Household income (percentage of population below a specified level)
- Households (52 programs, \$89.5 billion)
 - Area median income (household income below a specified percentage of AMI)

33. **I have identified 52 census-derived datasets used to geographically allocate federal spending.** (See schematic below.)



34. Eight datasets can be considered **foundational**. The remaining 44 datasets are **extensions** of these. Some extensions are **general**, in that they are used by multiple programs, and some are **program-specific**.

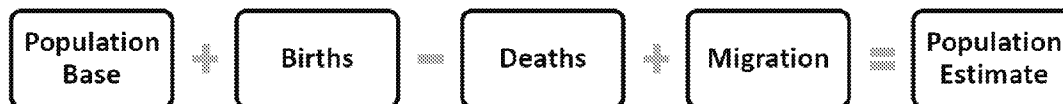
35. One foundational dataset is the Census Bureau's **Urban-Rural Classification** of every census tract based on Decennial Census population density. (The minimum density for an urban designation is 1,000 persons per square mile.) The Census Bureau publishes the Urban-Rural Classification once a decade (in the year ending in "2"). This classification is the primary

basis for other geographic classifications. It is the only census-derived dataset that relies solely on decennial numbers.¹⁶

36. The Office of Management and Budget (OMB) delineates county-based **Core-based Statistical Areas (CBSAs)** — metropolitan areas and micropolitan areas. CBSAs are delineated around urban “cores” designated by the Urban-Rural Classification.¹⁷

37. The other six foundational datasets are multivariate—that is, they provide census-derived data on multiple socioeconomic variables such as race, age, poverty, occupation, and housing costs.

38. Two of these are **augmented datasets**. The Census Bureau constructs annual **Population Estimates** and **Housing Estimates** by augmenting decennial population and housing numbers with more recent data, primarily from vital statistics and tax records. For example, the Census Bureau annually updates Population Estimates by taking the previous year’s numbers (starting with the decennial year) and adding births, subtracting deaths, and estimating net domestic and international migration.¹⁸



¹⁶ The Census Bureau identifies two types of urban areas—urbanized areas (UAs) that contain 50,000 or more people and urban clusters (UCs) with a population of at least 2,500 and less than 50,000. By definition, any census tract that is not in a UA or UC is “rural.” Detailed information on the Census Bureau’s Urban-Rural Classification, including methodology, is available at <https://www.census.gov/geo/reference/urban-rural.html>.

¹⁷ OMB delineations of metropolitan and micropolitan areas and the 2010 standards on which they are based can be found at <https://www.census.gov/programs-surveys/metro-micro.html>. In the CBSAs framework, metropolitan areas have a UA as the core and micropolitan areas have a UC as the core. Each CBSA contains one or more central counties (the ones containing the UA or UC) plus any outlying counties economically integrated with the central counties, as measured by commuting flows. “Non-core” means any county not in a CBSA.

¹⁸ Detailed information on the Census Bureau’s Population and Housing Unit Estimates, including methodology, is available at <https://www.census.gov/programs-surveys/popest.html>.

39. The Census Bureau uses a similar method to annually update Housing Estimates. Each of the variables in Population Estimates and Housing Estimates is on the decennial data collection form.

40. Population Estimates are frequently used directly to determine funds distribution, for instance, according to each state's share of the most recent U.S. population total. They also enable the creation of economic indicators that allow geographic areas to be compared regardless of size. A good example is state Per Capita Income (PCI), which is determined by dividing state Personal Income by state population (from Population Estimates).

41. The remaining four foundational datasets are produced through ongoing **household surveys** that collect information on demographic variables not on the decennial questionnaire (such as income, health insurance coverage, and housing costs). The Census Bureau relies on the Decennial Census to design and implement the **American Community Survey (ACS)**, the **Current Population Survey (CPS)**, the **Consumer Expenditure Survey (CEX)**, and the **American Housing Survey (AHS)**.¹⁹ It does so in five ways, as described in the table on the next page.

42. The two augmented datasets and the four household surveys are intertwined. In particular, the international in-migration component of Population Estimates comes from the ACS.²⁰ At the same time, Population Estimates are used as controls in the design and implementation of the household surveys.

¹⁹ The Census Bureau conducts the CEX on behalf of BLS.

²⁰ Census Bureau, "Methodology for the United States Population Estimates: Vintage 2017, Nation, States, Counties, and Puerto Rico—April 1, 2010 to July 1, 2017," p. 10, available at <https://www2.census.gov/programs-surveys/popest/technical-documentation/methodology/2010-2017/2017-natstcpr-meth.pdf>.

43. The eight foundational census-derived datasets enable the creation of 44 extension datasets. These include:

- **Geographical classifications** (six general, 14 program-specific) – The classification of geographic units (such as census tracts and counties) on the basis of some combination of population density (e.g., urban/rural), population size, and commuting patterns (e.g., metropolitan and micropolitan statistical areas).
- **Standard economic indicators** (five general) – Widely-recognized measures of economic conditions (such as inflation, personal income, unemployment rate, and poverty rate) that can be used to guide a multitude of assistance programs.
- **Program-specific measures** (19) – Measures of specific economic conditions specifically created to administer a particular financial assistance program, for example, Section 8 housing vouchers and Title I grants to local education agencies.

| The Roles of the Decennial Census in Household Survey Design and Analysis | |
|--|---|
| Sampling frame | The Census Bureau’s Master Address File (MAF), the underpinning of the Decennial Census operation, provides the frame from which a survey sample is drawn. ²¹ |
| Sample design | The Decennial Census guides sample design in two ways. One is by delineating the primary sampling units from which samples are to be drawn and the sampling rates by which they are drawn. The second is to guide sample stratification, that is, the size of subsamples by characteristics such as race and household composition. ²² |

²¹ See, for example, Census Bureau, “Chapter 3. Frame Development” in “American Community Survey: Design and Methodology,” January 2014.

²² See, for example, Danielle Neiman, Susan King, David Swanson, Stephen Ash, Jacob Enriquez, and Joshua Rosenbaum, “Review of the 2010 Sample Redesign of the Consumer Expenditure Survey,” presented at the Joint Statistical Meetings, October 2015.

| | |
|------------|--|
| Imputation | Nonresponses to individual questions are filled in by imputing, or “borrowing,” answers from other households with similar characteristics. ²³ |
| Weighting | In preparing survey estimates, the weight of each household’s response is determined in relation to the estimated overall number of households and the estimated number of residents of similar age, sex, race, and Hispanic origin, as derived from the Decennial Census through annual population and housing estimates. ²⁴ |
| Variance | To understand the reliability of any survey result, the survey sponsors need to produce estimates of variance, or sampling error, which also is based annual population and housing estimates. ²⁵ |

44. Census-guided financial assistance programs use census-derived datasets to differentiate among geographic areas in terms of eligibility and/or allocation and then distribute funds based on those differentiations.

V. CONCLUSION

45. Across the breadth of census-guided programs, geographic differences in the accuracy of the Decennial Census will lead to distortions in the distribution of financial assistance. That said, the sensitivity of funds distribution to census mismeasurement is by far the greatest for programs with geographic allocation formulas that rely on census-derived data. Allocation formulas reflect a continuum of possible outcomes – place on that continuum is determined by specific statistics, often calculated to the one-hundredth or one-thousandth of a percent point. Even modest geographic differences in census accuracy can lead to changes in funds distribution.

²³ See, for example, Census Bureau, “Section 10.6: Editing and Imputation” in “American Community Survey: Design and Methodology,” January 2014.

²⁴ See, for example, Census Bureau, “Chapter 11: Weighting and Estimation,” in “American Community Survey: Design and Methodology,” January 2014.

²⁵ See, for example, Census Bureau, “Chapter 14: Estimation of Variance” in “Current Population Survey: Design and Methodology,” Technical Paper 66, October 2006.

46. Based on my experience and knowledge, when a state, county, or community loses population share due to a differential undercount, it receives less federal funding and its residents experience less access to valued programs and services than they otherwise would have received and/or face higher taxes than they otherwise would have paid.

I declare under penalty of perjury that the foregoing is true and correct.

A handwritten signature in black ink, appearing to read "Andrew Reamer", is positioned above a horizontal line.

Andrew Reamer

Executed on August 31, 2020 at Washington, D.C.

ANDREW D. REAMER, Ph.D.

George Washington Institute of Public Policy
George Washington University
805 21st St., NW Suite 613
Washington, DC 20052

areamer@gwu.edu
(202) 994-7688

Education

- Ph.D. in Economic Development and Public Policy, Department of Urban Studies and Planning, Massachusetts Institute of Technology (1987)
- Master in City Planning, Department of Urban Studies and Planning, Massachusetts Institute of Technology (1981)
- Bachelor of Science in Economics, cum laude, Wharton School, University of Pennsylvania (1971)

Professional Experience

Research Professor, George Washington Institute of Public Policy, George Washington University (2011-present)

Focus on policies that encourage and support U.S. economic competitiveness. Areas of interest include innovation, regional economic and workforce development, and economic statistics.

Advisory Committees

- Member, U.S. Bureau of Economic Analysis Advisory Committee (2008-present)
- Member, Workforce Information Advisory Council, U.S. Department of Labor (2016-present)
- Member, Statistics Committee, National Association for Business Economics (2013-present)
- Member, Data User Advisory Committee, U.S. Bureau of Labor Statistics (2009-2018, chair 2009-2011)
- Member, National Advisory Committee on Innovation and Entrepreneurship, U.S. Department of Commerce (2016-2018)
- Member, Panel on Communicating National Science Foundation Science and Engineering Information to Data Users, Committee on National Statistics, National Research Council (2010-2011)

Publications

- “Comprehensive Accounting of Census-Guided Federal Spending (FY2017)—Part A: State Estimates,” Report #7B of the Counting for Dollars Project, February 2020
- “Federal Sources of Entrepreneurship Data: A Compendium,” for the E.M. Kauffman Foundation, December 2019
- “Comprehensive Accounting of Census-Guided Federal Spending (FY2017)—Part A: Nationwide Analysis,” Report #7A of the Counting for Dollars Project, November 2019

- “The Distribution of Census-Guided Federal Funds to U.S. Communities: Five Program Examples,” with Sean Moulton, Report #6 of the Counting for Dollars Project, July 2019
- “Distribution of Funding from 55 Large Census-guided Programs by State,” Report #5 of the Counting for Dollars Project, May 2019
- “Census-derived Datasets Used to Distribute Federal Funds,” Report #4 of the Counting for Dollars Project, December 2018
- “Federal Funding for Rural America: The Role of the Decennial Census,” Report #3 of the Counting for Dollars 2020 Project, December 2018
- “Company Outcomes Research for Evaluating SBIR (CORES),” with Robin Gaster, for the National Science Foundation, May 2018
- “Nationwide Data Initiative: Principles of Approach to Organizational Design and Development,” for the US Partnership on Mobility from Poverty, April 2018
- “Counting U.S. Secondary and Postsecondary Credentials,” co-author with Center for Regional Economic Competitiveness, for Credential Engine, April 2018
- “Counting for Dollars 2020: The Role of the Decennial Census in the Geographic Distribution of Federal Funds – Report #2: Estimating Fiscal Costs of a Census Undercount to States,” March 2018
- “A Roadmap to a Nationwide Data Infrastructure for Evidence-Based Policymaking,” with Julia Lane, *The ANNALS of the American Academy of Political and Social Science*, Vol 675, Issue 1, 2018
- “Before the U.S. Tariff Commission: Congressional Efforts to Obtain Statistics and Analysis for Tariff-setting, 1789–1916,” chapter for *Centennial History of the United States International Trade Commission*, November 2017
- “Toward A U.S. Competitiveness Strategy,” *Innovations: Technology, Governance, Globalization*, Policy Design issue, Summer-Fall 2017, Volume 11, Issue 3-4
- “Counting For Dollars: The Role of the Decennial Census in the Geographic Distribution of Federal Funds Initial Analysis: 16 Largest Census-guided Programs,” August 2017.
- “Federal Efforts in Support of Entrepreneurship: A Reference Guide,” prepared for the Kauffman Foundation, April 2017
- “Better Jobs Information Benefits Everyone,” *Issues in Science and Technology*, v. 23, n. 1, Fall 2016, pp. 58-63.
- “Data Resources to Support Middle-Skill Workforce Development,” research paper prepared for Committee on the Supply Chain for Middle-Skill Jobs: Education, Training and Certification Pathways, Board on Science, Technology and Economic Policy, National Academy of Sciences, August 2015
- “Analyzing Talent Flow: Identifying Opportunities for Improvement,” with Robert Sheets and David Stevens, for the Talent Pipeline Management Initiative of the Center for Education and Workforce, U.S. Chamber of Commerce Foundation, July 2015

- “Stumbling into the Great Recession: How and Why GDP Estimates Kept Economists and Policymakers in the Dark,” GWIPP research note, April 2014
- “Indicators of the Capacity for Invention in the United States,” research paper prepared for the Lemelson Foundation, March 2014
- “The Impacts of Technological Invention on Economic Growth – A Review of the Literature,” research paper prepared for the Lemelson Foundation, February 2014
- “National Nonprofit Organizations That Inspire and Enable Invention and Invention-based Enterprises,” research paper prepared for the Lemelson Foundation, February 2014
- “Global Entrepreneurship Week Policy Survey,” report, Public Forum Institute, November 2013
- “Improving Federal Statistics for Industry Studies,” research paper presented at Industry Studies Association annual conference, Kansas City, Missouri, May 2013
- “Using Real-time Labor Market Information on a Nationwide Scale,” policy brief, Credentials That Work Initiative, Jobs for the Future, April 2013
- “Labor Market Information Customers and Their Needs: Customer-Oriented LMI Product Innovation,” with Center for Regional Economic Competitiveness, report for the Customer Consultation Study Group, Workforce Information Council, April 2012
- “Economic Intelligence: Enhancing the Federal Statistical System to Support U.S. Competitiveness,” policy brief, Series on U.S. Science, Innovation, and Economic Competitiveness, Center for American Progress, February 2012
- “Say Goodbye to the Survey of Business Owners?,” Policy Forum Blog, the Policy Dialogue on Entrepreneurship, September 26, 2011.
- “The Quality of Economic Statistics is About to Erode,” Policy Forum Blog, the Policy Dialogue on Entrepreneurship, September 19, 2011
- “Putting America to Work: The Essential Role of Federal Labor Market Statistics,” article, AMSTAT News, American Statistical Association, March 1, 2011
- “The Federal Role in Encouraging Innovation: The “I’s” Have It,” article, Innovation Policy Blog, December 18, 2010

Congressional and Other Public Testimony

- “The Economic Impacts of the 2020 Census and Business Uses of Federal Data,” testimony to the Joint Economic Committee, U.S. Congress, May 22, 2019
- “The Evolution of the Federal Statistical System: Implications for Evidence-based Policymaking,” testimony to the Commission on Evidence-based Policymaking, March 13, 2017
- “The American Community Survey: Approaches to Addressing Constituent Concerns,” testimony before the Subcommittee on Federal Financial Management, Committee on Homeland Security and Government Affairs, U.S. Senate, Washington, DC, July 18, 2012

- “The Economic Impact of Ending or Reducing Funding for the American Community Survey and Other Government Statistics,” testimony before the Joint Economic Committee, U.S. Congress, Washington, DC, June 19, 2012
- Testimony on the President’s FY2012 Budget before the House Appropriations Subcommittee on Commerce, Justice, Science, and Related Agencies, Washington, DC, March 11, 2011

Public Presentations

- “Role of the 2020 Census in the Geographic Allocation of Federal Spending,” presented at Council of Professional Associations on Federal Statistics, March 6, 2020.
- “Role of the 2020 Census in the Geographic Allocation of Federal Spending,” presented at National Association of Counties Legislative Conference, March 2, 2020.
- “Census-Guided Federal Spending: A Comprehensive Accounting,” presented at National League of Cities, November 18, 2019.
- “The Role of the 2020 Census in the Geographic Distribution of Federal Funds,” presented at annual conference of Association of Public Data Users, July 10, 2019
- “Making it Count: The Role of the 2020 Census in the Geographic Distribution of Federal Funds by County,” webinar presentation to the National Association of Counties, June 13, 2019
- “The Role of the 2020 Census in Distributing Federal Funds to Metro Washington,” presented at “Interventions that Work: 2020 Census & Hard-to-Reach Communities,” Washington, DC, June 6, 2019
- “Non-traditional Datasets for Research on Entrepreneurship,” presentation at Industry Studies Association annual conference, May 31, 2019
- “The Census, SCOTUS & The Economy,” podcast interview, Joint Economic Committee Democrats, recorded May 22, 2019, released May 30, 2019
- “The Role of the ACS in the Distribution of Federal Funding,” presented at the ACS Data Users Conference, Washington, DC, May 14, 2019
- “The Role of the 2020 Census in Distributing Federal Funds to Maryland Nonprofits,” presented to Maryland Nonprofits, March 20, 2019
- “Counting for Dollars: A Study of Census-guided Financial Assistance to Rural America,” presented to the Congressional Rural Caucus, U.S. House of Representatives, Washington, DC, October 11, 2018
- “2020 Census: How the Count Affects State Budgets,” presented to the National Association of State Budget Officers (NASBO) annual conference, Oklahoma City, Oklahoma, July 23, 2018
- “Company Outcomes Research for Evaluating SBIR (CORES),” presentation at Association of Public Data Users annual conference, July 18, 2018
- “Preparing for the Census: What’s in Store for 2020 – Why the Census Matters to Cities,” presentation to National League of Cities annual conference, March 13, 2018

- “Counting for Dollars: The Role of the Decennial Census in the Geographic Distribution of Federal Funds,” presented to the Council of Professional Associations for Federal Statistics, September 15, 2017
- “Congressional Attitudes to Evidence-based Policymaking: An Historical Review,” presentation to Legislative Branch Capacity Working Group, July 17, 2017
- “Before the U.S. Tariff Commission: Congress’ Efforts to Obtain Statistics and Analysis for Tariff-setting, 1789-1916,” presentation to Industry Studies Association annual conference, May 26, 2017
- “A Compendium of Federal Efforts to Support Entrepreneurship: Assessment and Implications,” Industry Studies Association annual conference, May 26, 2016
- “Communicating the American Community Survey’s Value to Respondents,” Committee on National Statistics, National Academy of Sciences, March 8, 2016.
- “The Mercantilist Policy Origins of Federal Economic Statistics Agencies,” History of Economics Society annual conference, June 27, 2015.
- “Data Resources to Support Middle-Skill Workforce Development,” Symposium on the Supply Chain for Middle-Skill Jobs: Education, Training and Certification Pathways, June 25, 2015.
- “Towards a Federal Strategy for U.S. Economic Competitiveness,” Industry Studies Association, May 27, 2015
- “Madison’s Legacy: Federal Statistical Products Based on the American Community Survey,” ACS Data Users Conference, May 12, 2015
- “Stumbling into the Great Recession: How and Why GDP Estimates Kept Economists and Policymakers in the Dark,” GW Forecasting Seminar, February 12, 2015
- “Efforts to Measure Trade in Value-Added and Map Global Value Chains: A Guide,” Industry Studies Association Annual Conference, Portland, Oregon, May 29, 2014
- “Stumbling into the Great Recession: How and Why GDP Estimates Kept Economists and Policymakers in the Dark,” presented to the U.S. Bureau of Economic Analysis Advisory Committee, Washington, DC, May 9, 2014
- “The Manufacturing Policy Origins of U.S. Economic Statistical Agencies,” presentation to the Manufacturing Council, U.S. Department of Commerce, Washington, DC, July 23, 2013
- “A Foundation to Measure U.S. Economic Competitiveness: Proposals,” presented at “Measuring Competitiveness: In Search of New Metrics” Luncheon, Bernard L. Schwartz Program in Competitiveness and Growth Policies, Carnegie Endowment for International Peace, Washington, DC, June 20, 2013
- “Sources and Uses of Federal Labor Market Information: Current Developments,” presentation to the Real-Time LMI Innovators Network, Jobs for the Future, Boston, MA, April 16, 2013
- “The Economic Census and Its Role in Economic Statistics,” 2012 Economic Census Conference, U.S. Census Bureau, Washington, DC, October 15, 2012

- “The Government's Role in Stimulating Clusters,” Workshop: Encouraging the Commercialization of Research Results and the Utilization of Cluster Mapping through EU-US Collaborations, Center for Transatlantic Relations, Johns Hopkins University, Washington, DC, December 7, 2011
- “Employment and Workforce Data Systems at the Federal Level: New Developments, Challenges, and Opportunities for Community Colleges,” presented to Real Time LMI Innovators Network, Jobs for the Future, Chicago, IL, November 29, 2011
- “Statistics for Cluster Analysis: Innovations and Opportunities,” presentation to the Taskforce for the Advancement of Regional Innovation Clusters (TARIC), U.S. Department of Commerce, Washington, DC October 24, 2011
- “Sub-National STI Statistics: Recommendations for the National Center for Science and Engineering Statistics,” presentation to panel on Developing Science, Technology, and Innovation Indicators for the Future, National Academies of Science, Washington, DC, July 12, 2011
- “Regional Clusters and Federal Economic Policy,” presentation to Manufacturing Industry Study Seminar, Industrial College of the Armed Forces, Washington, DC, March 22, 2011
- “Innovations in Federal Statistics: New Views on Regions,” presented to Understanding, Using, and Maximizing New Federal Data Workshop, IEDC 2011 Federal Economic Development Forum, March 20, 2011
- “The Changing Landscape of Federal Workforce Statistics: The Context for Real-Time LMI,” presentation to Credentials That Work workshop, Jobs for the Future, Washington, DC, March 15, 2011
- “Putting America to Work: The Essential Role of Federal Labor Market Statistics,” presentation to Local Employment Dynamics Partnership Workshop, Washington, DC, March 9, 2011

Hosted Public Events

- “Innovative Data Sources for Regional Economic Analysis,” conference and symposium, Washington, DC, May 7-9, 2012
- “Roundtable on Science, Technology, and Innovation Data and Indicators,” Washington, DC, June 29, 2011

Public Resource Material

- “Education and Workforce Data Resources,” LMI Institute, Fall 2014
- “Public and Private Sources of Education and Workforce Data,” April 2014
- “Resources Regarding the American Community Survey (ACS) of the U.S. Census Bureau,” May-December 2012

Reports to Clients for Internal Use

- “Federal Manufacturing Policy: An Historical Overview,” reference paper prepared for the U.S. Department of Commerce, August 2013

- Papers and reports prepared with the University of North Carolina for “Evaluation and Assessment of Economic Development Investments,” a cooperative project with the U.S. Economic Development Administration, October 2011-December 2013
- Analyses prepared for the Panel on Developing Science, Technology, and Innovation Indicators for the Future, Committee on National Statistics in collaboration with the Board on Science, Technology, and Economic Policy, National Research Council, April 2011-December 2012.

Fellow, Metropolitan Policy Program, The Brookings Institution (2006-2010)

Managed the Federal Data Project, an effort that encouraged the federal government to produce the current, accurate, detailed geographic data needed by public and private decision-makers and researchers. Priorities included economic statistics, demographic statistics, and federal expenditures data. Methods include congressional testimony and briefings, public presentations, written and oral communications with federal statistical organizations, public and roundtable events, statistical system stakeholder network development, participation in statistical agency advisory committees, and data product development.

Examples of efforts included:

- Economic Statistics
 - “Putting America to Work: The Essential Role of Federal Labor Market Statistics” (2010)
 - Economic data roundtables with federal statistical agencies, professional and trade associations, policy research organizations, and federal program agencies (2008-2010)
 - Regarding Census Bureau’s Local Employment Dynamics program – congressional briefings, annual conference and leadership meetings, panel session participation (2006-2010)
 - “Measuring Up in a Changing Economy: A Look at New U.S. Service Sector Data and Why It Matters,” public event and roundtable (2010)
 - Who Cares About Economic Statistics,” *Dismal Scientist*, Moody’s Economy.com (2009)
 - “The Structure of the U.S. Economic Statistical System: Implications for Public Policy,” presentation to the International Statistical Institute conference, Durban, South Africa (2009)
 - “In Dire Straits: The Urgent Need to Improve Economic Statistics,” *AmStat News* (2009)
 - “Ensuring Economic Programs Accurately Reflect the 21st Century,” speech to the Census Bureau Economic Programs Directorate leadership off-site (2008)
 - “The Department of Commerce Budget Request for Fiscal Year 2008: Observations for Consideration,” testimony before the House Committee on Appropriations, Subcommittee on Commerce, Justice, Science and Related Agencies (2007)

- Demographic Statistics
 - “Surveying for Dollars: The Role of the American Community Survey in the Geographic Distribution of Federal Funds” (2010)
 - “Counting for Dollars: The Role of the Decennial Census in the Geographic Distribution of Federal Funds” (2010)
 - “The Federal Statistical System in the 21st Century: The Role of the Census Bureau,” testimony before the Joint Economic Committee (2009)
 - “Tempest Over the Census,” Brookings editorial (2009)
 - Prototype database to determine geographic allocation of federal funds (counties, metros, states) on the basis on census statistics (2008-09)
 - Prototype tool to provide maps and tables on “hard-to-count” census tracts throughout the U.S. (2008-09)
 - Communications with OMB and Census Bureau leading to improved decennial census enumeration of households in small multi-unit buildings without traditional city-style addresses (2006-09)
 - Census Bureau-data user roundtables on improving Census Bureau’s American Community Survey data products (2007-08)
 - “Preparations for 2010: Is the Census Bureau Ready for the Job Ahead?,” testimony before the Senate Committee on Homeland Security and Governmental Affairs Subcommittee on Federal Financial Management, Government Information, Federal Services, and International Security (2007)
 - “The 2010 Census: What State, Local, and Tribal Governments Need to Know,” workshop (2007)
- Federal Spending Transparency and Accountability
 - “Metro Potential in ARRA: An Early Assessment of the American Recovery and Reinvestment Act” (with Mark Muro, Jennifer Bradley, Alan Berube, Robert Puentes, and Sarah Rahman), chapter on transparency (2009)
 - Memos to and meetings with Congress and the Office of Management and Budget (OMB) on the design and implementation of the Federal Financial Accountability and Transparency Act of 2006 and American Recovery and Reinvestment Act (2007-09)
 - “OMB’s Congressional Mandates to Provide Information on Federal Spending,” presentations to the National Grants Partnership (2007) and National Academies of Science (2008)

Prepared briefs, articles, presentations, and testimony on federal economic development policy.

- “Stimulating Regional Economies: the Federal Role,” presented at Growing Innovation Clusters for American Prosperity symposium, National Academy of Sciences (2009)

- Congress Directs EDA to Act on Clusters,” *The New Republic* blog post (with Mark Muro, 2009)
- “Clusters and Competitiveness: A New Federal Role for Stimulating Regional Economies” (with Karen Mills and Elisabeth Reynolds, 2008)
- “The Department of Commerce Budget Request for Fiscal Year 2008: Observations for Consideration,” testimony before the House Committee on Appropriations, Subcommittee on Commerce, Justice, Science and Related Agencies (2007)
- “The Federal Role in Regional Economic Development,” testimony before the House Committee on Transportation and Infrastructure, Subcommittee on Economic Development, Public Buildings, and Emergency Management (2007)
- “How Economic Change Happens and Why We Resist It,” speech before the Symposium on Change, University of Buffalo Regional Institute (2007)

Deputy Director and Fellow, Urban Markets Initiative, The Brookings Institution (2004-06)

Guided a foundation-funded effort to increase the availability and accessibility of data on urban neighborhoods. Projects managed included:

- Federal data agenda – identifying ways in which the federal government can improve availability and accessibility of statistics for states, metro areas, cities, and neighborhoods
- National Infrastructure for Community Statistics – managing a Community of Practice (CoP) focused on the development of a nationwide infrastructure to provide widespread access to data from multiple sources on multiple topics
- Urban budgets – creating a tool to ascertain the flow of federal investments by type of investment and by county

Examples of efforts included:

- “To Take a Bite Out of Crime: Safeguard the Census,” *Brookings Alert* (2006)
- “Anticipating the Unimaginable: The Crucial Role of the Census in Disaster Planning and Recovery,” *Brookings Alert* (2006)
- “Apportionment in the Balance: A Look into the Progress of the 2010 Decennial Census,” testimony before House Committee on Government Reform (2006)
- “Better Data for Better Decisions: The Value of the American Community Survey to the Nation,” Brookings Briefings on the Census (2006)
- “The Road to 2010: Plans for the 2010 Census and the American Community Survey,” Brookings Briefings on the Census (2006)
- “Federal Statistics: Robust Information Tools for the Urban Investor” (with Pari Sabety, 2005)

Principal, Andrew Reamer & Associates (full-time 1995-2004, part-time 2004-present)

Promotes sound public policy and effective economic development through three sets of activities:

- Building Capacities for Producing and Using Regional Socioeconomic Data
- Indicator Systems Design and Implementation
- Regional Economic Development Analysis, Strategy, and Program Development

Building Capacities for Producing and Using Regional Socioeconomic Data

- Determining Public and Private Sector Needs For Socioeconomic Data
 - Federal Data Agenda, Urban Markets Initiative, Brookings Institution (consultant, 2004). Managed staff assessments of 30 federal statistical agencies to determine issues and barriers to providing data useful for urban market decisions, and priorities for action to address these issues and barriers.
 - Socioeconomic Data for Economic Development: An Assessment (with Joseph Cortright, for U.S. Economic Development Administration, 1999)
- Mechanisms to Enhance Economic Markets Through Improved Data Development, Access, and Use
 - Guides
 - Socioeconomic Data for Understanding Your Regional Economy: A User's Guide (with Joseph Cortright, for U.S. Economic Development Administration, 1998)
 - Web sites
 - WorkforceUSA (adviser to Workforce Learning Strategies, for U.S. Department of Labor and Ford Foundation, 2002)
 - Mapstats (adviser to Mapstats Working Group, FedStats Task Force, 2000-01)
 - EconData.Net (co-developer and –owner, with Joseph Cortright, 1999-present). Econdata.Net is a portal to 1,000 on-line sources of regional socioeconomic data, organized by topic and provider. The site has 14,000 visitors monthly, and 3,000 subscribers to a monthly newsletter, StatScan. EconData.Net was developed and operated using Economic Development Administration funds, and is now sponsored by the Fannie Mae Foundation.
 - CDs
 - R-Maps, Office of Policy Development and Research, U.S. Department of Housing and Urban Development (facilitator of development of CD with PD&R data sets and LandView mapping tool, 2000-01)

- Conference Design and Development
 - America’s Scorecard: The Historic Role of the Census Bureau in an Ever-Changing Nation, Woodrow Wilson International Center for Scholars, Washington, DC (for Census Bureau, March 2004)
 - International Conference on Community Indicators, Community Indicators Consortium, Reno, Nevada (March 2004)
 - Next Generation of Community Statistical Systems, Tampa, Florida (with University of Florida, for Ford Foundation, March 2002)
 - Innovations in Federal Statistics, Woodrow Wilson International Center for Scholars, Washington, DC (for the Center, May 2001)
- Organizational and Professional Network Development and Management
 - Community Indicators Consortium (conference track chair, planning committee chair, 2004)
 - Community Statistical Systems Network (2002 – 04)

Indicator Systems Design and Implementation

- Working Poor Families Project, Annie E. Casey Foundation/Ford Foundation/Rockefeller Foundation (with Brandon Roberts + Associates, 2001 – present)
 - Annually oversee the preparation of state indicators on the economic conditions and characteristics of working families and individuals
 - With Brandon Roberts, advised state advocacy organizations (15 to date) in the preparation of policy reports on low-income working families
 - Co-authored one national report (2004) and advised on second (2008)
- “Development Report Card for the States,” Corporation for Enterprise Development (1987 – 2006)
 - Annually prepared indicators on economic vitality for the 50 states
 - Advised on revisions of indicators framework

Regional Economic Development Analysis, Strategy, and Program Development

- Nationwide Analysis Of Regional Economic Dynamics and Programs
 - Technology Transfer and Commercialization: Their Role in Economic Development (for Economic Development Administration, 2003) – Note Chapter Three and Appendix B on the geography of innovation in the U.S.

- Guides
 - Strategic Planning in the Technology-Driven World: A Guidebook for Innovation-Led Development, Collaborative Economics (co-author with Jennifer Montana, for Economic Development Administration, 2001)
- Regional Economic Analysis, Strategy, and Program Development (see next section)

Other Prior Professional Experience – Regional Economic Development

As co-founder and principal of Mt. Auburn Associates (1984-1995) and as principal of Andrew Reamer & Associates (1995-present), Andrew Reamer managed and participated in regional economic development studies of three types: analysis and strategy, program evaluation, and program design

Analysis and Strategy

- General Regional Economic Development Analyses and Strategies

Involved in over 30 general economic development studies, clients include:

 - States of Massachusetts, Rhode Island, Arkansas, Indiana, Georgia, and Colorado
 - Regions in western Massachusetts, northeast and northwest Connecticut, northern New Mexico, northwest Oregon
 - Metro areas of Boston, Worcester, and Springfield, Massachusetts; Nashua, New Hampshire; Indianapolis, Indiana; Memphis, Tennessee; Shreveport, Louisiana; Austin, Texas
 - Cities of Boston, Massachusetts, Dublin, Ohio, and Collierville, Tennessee
 - Clarke County, Georgia and Aiken County, South Carolina
- Regional Industry Competitive Analyses and Strategies
 - Examined competitive strengths, weaknesses, and strategy options for specific regional industries, include fiber optics, telecommunications, information technology, advanced materials, software, metalworking, environmental technology, marine technology, biomedical, food processing, footwear, plastics, oil, natural gas, petrochemicals, wood products, warehousing and distribution, and heavy vehicles.
- Advanced Technology Analyses and Strategies
 - Analyzed key technology industries and development opportunities in Iowa and Virginia

- Prepared regional strategies for promoting technology transfer from the Los Alamos National Laboratory, the Department of Energy Jefferson National Accelerator Facility, and the Air Force's Rome Laboratory. Regional Defense Adjustment Efforts
 - Managed or participated in the preparation of conversion strategies for defense-dependent regions, facilities reuse plans, and base closure impact analyses.
- Recyclable Material Markets Analyses and Strategies
 - Managed or participated in preparation of analyses and strategies in New York, Pennsylvania, Massachusetts, Connecticut, Rhode Island, Texas, North Carolina, Mississippi, and Iowa.

Program Evaluation

- Evaluation Of Federal Economic Development Programs
 - Managed or participated in evaluation of the U.S. Economic Development Administration's Revolving Loan Fund, Technical Assistance, Public Works, and Small Business Incubator programs.
 - Managed two evaluations of the Jobs Through Recycling program of the U.S. Environmental Protection Agency.
- Evaluation of State Economic Development Programs
 - Managed or participated in evaluation of Ohio's Edison Technology Centers and technology transfer intermediaries, New York's Office of Recycling Market Development, Iowa's small business incubator program, Oregon's Regional Strategy program, Georgia's economic development agencies, and Massachusetts' Community Development Finance Corporation.

Program Design

- Design Of State And Individual Small Business Incubator Programs
 - Managed program-specific efforts for the states of Massachusetts and Iowa and facility-specific efforts in New Mexico and Massachusetts.
- Design Of State Defense Industry Conversion Programs
 - For the National Governors Association, participated in the development of state defense industry conversion programs in Massachusetts, Rhode Island, and Virginia.

Chronology of Professional Experience

- Research Professor, George Washington Institute of Public Policy, George Washington University (2011-present)
- Nonresident Senior Fellow, Metropolitan Policy Program, The Brookings Institution (2010-2013)
- Fellow, Metropolitan Policy Program, The Brookings Institution (2005-2010)
- Deputy Director and Fellow, Urban Markets Initiative, Metropolitan Policy Program, The Brookings Institution (2004-06)
- Principal, Andrew Reamer & Associates (full-time 1995-2004, part-time 2004-present)
- Lecturer, Department of Urban Studies and Planning, Massachusetts Institute of Technology (1986, 2002-04)
- Principal, Mt. Auburn Associates (1984-1995)
- Case Team Member, Rhode Island Strategic Development Commission (1983-84)
- Consultant, Counsel for Community Development (1982-83)
- Graduate instructor, MIT Department of Urban Studies and Planning (1981-82)
- Policy Analyst, U.S. Department of Commerce, Office of the Assistant Secretary for Policy (1980)
- Research Assistant, MIT Center for Transportation Studies (1981-82)
- Research Assistant, MIT Energy Laboratory (1978-1981)
- Health Planner, Maryland Health Planning and Development Agency (1975-78)
- Administrative Assistant, Johns Hopkins Hospital (1974)
- Research Analyst, Boston Urban Observatory, University of Massachusetts (1973)
- Summer Intern, Mayor's Office of Public Service, City of Boston (1970, 1971)

Achievements and Honors

- Doctoral Fellow, Harvard-MIT Joint Center for Urban Studies (1983-1984)

Professional Affiliations

- Association of Public Data Users, Past President (2011-2012), President (2009-2010), Vice President (2008), Board member (2006-2007)
- Council for Community and Economic Research, Board member (2007- 2012)
- National Association for Business Economics, Member of Statistics Committee (2013-present)
- American Statistical Association
- American Economic Association
- History of Economics Association

EXHIBIT E

UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF MARYLAND

LA UNIÓN DEL PUEBLO ENTERO, et al.,

Plaintiffs,

v.

DONALD J. TRUMP, sued in his official capacity
as President of the United States, et al.,

Defendants.

Civil Action No. 8:19-CV-02710-PX

DECLARATION OF KIMBALL W. BRACE

I. INTRODUCTION

1. I am the president of Election Data Services, Inc. (E.D.S. Inc.), a Manassas, Virginia-based consulting firm whose specialty is reapportionment, redistricting matters, election administration issues, and the census.

2. I have been retained by the plaintiffs in *La Union del Pueblo Entero v. Trump et al.*, Case No. 8-19-cv-02710 (D. Md.). I have been asked to assess the impact of a truncated Census field operation and post-processing operation on (i) the apportionment of Congressional seats following the 2020 Census, and (ii) the dilution of the votes of people living in certain counties as a result of intrastate redistricting.

3. All the materials considered in forming the opinions contained herein are identified in this report. I am being compensated for my work on this matter at an hourly rate of \$175, while members of my staff at billed at \$140 per hour.

II. BACKGROUND AND QUALIFICATIONS

4. I attended American University in Washington, D.C., from 1969 through 1974 (having taken a year off for the 1972 campaign), where I earned a B.A. degree in Political Science. I started E.D.S. Inc. in 1977 and have been with the company since that time.

5. Prior to 1977, I was a journalist and employed by companies like NBC News, Congressional Quarterly, and Plus Publications. While I was with NBC News, I was a researcher, advance man, and, during the 1972 election year, an election analyst for the NBC News Elections Unit. One of my responsibilities was to follow the redistricting process that occurred after the 1970 census. At Congressional Quarterly, I was in charge of congressional voting studies. At Plus Publications, I was Associate Editor of a newsletter called *Election Administration Reports*, a bi-weekly publication for state and county election administrators and registrars of voters. A copy of my curriculum vitae is attached as **Exhibit 1**.

6. As president of E.D.S. Inc., I supervise and direct all major projects in which the company is involved.

7. E.D.S. Inc. is a research facility and consulting firm dealing with many aspects of the electoral process. The company and its staff have been hired by state and local governments across the nation to provide software, database development services, and consulting services for the creation of districting plans and the analysis of many aspects of the apportionment and redistricting process.

8. Since 1979, I, individually and with E.D.S. Inc., have been actively involved in many aspects of the redistricting and reapportionment process, having gone through four full census and redistricting cycles. We have already been retained by several states for the planning and database activities associated with the 2020 redistricting process. I have been a consultant to many state and local governmental organizations around the nation, providing strategic advice and consulting on redistricting matters, coordinating the development of the databases used in the

redistricting process, creating and assisting others with the creation of districting plans, and analyzing many aspects of districts and district configurations.

9. Over the past 39 years, E.D.S. Inc.'s clients for redistricting services have come from more than half the states in the nation. In addition, over the past three decades, I have been called upon to provide reports, expert witness testimony, and assistance to attorneys in more than 70 different court cases.

10. Further, I frequently give speeches to groups and organizations and participate in numerous conferences and panels on various aspects of apportionment, redistricting, and the census. Since the early 1980s, I have been a regular participant and speaker at annual and bi-annual meetings of the Task Force on Redistricting of the National Conference of State Legislatures ("NCSL"). I have also been on their faculty, as NCSL has conducted five regional "Get Ready for Redistricting" seminars each decade since 1980. I was also appointed by the U.S. Secretary of Commerce to the 2010 Census Advisory Committee, a 20-person advisory board to the Director of the Census Bureau and served for two terms. Earlier this year I was asked to be NCSL's representative on a series of half-day small-group expert meetings, being arranged by the Committee on National Statistics (CNSTAT), to delve deeply into and provide informal discussion/feedback with Census Bureau staff as they continue to develop the differential privacy-based Disclosure Avoidance System for the 2020 census. I am regularly called upon by members of the press with questions on redistricting, reapportionment, the census, election administration issues, and politics in general.

11. In addition to its redistricting work, E.D.S. Inc. provides assistance in the election administration field to state and local jurisdictions in such areas as precinct management, voter registration systems, and voting equipment evaluation. E.D.S. Inc. regularly collects election returns for each state in the nation. In 1992, the company published a 500-page volume of county-level voter registration and voter turnout data, and election returns for the entire nation

(The Election Data Book: A Statistical Portrait of Voting in America, 1992 (Bernan Press, 1993)). While we only published the single volume, we have continued to compile an electronic county-level database for each general election since that time, which we sell to numerous institutions and organizations.

12. I personally have been involved in the election administration field for over 40 years. I have worked for federal government clients (Federal Election Commission, Election Administration Commission, GAO, Library of Congress) along with a number of state governments on different aspects of election administration. These include studies on voter registration systems as well as voting equipment.

13. Since 2008, I have been a poll worker in Prince William County, VA where I live. Because the state holds elections every year and due to my interest in all aspects of election administration, I have graduated to now being “chief judge” in the precincts that I have been assigned to work. In 2012, the county experienced long lines at the polls on Election Day, and I was then appointed to a 20-person task force by the County Board of Supervisors to investigate the cause of the problems. Because of my data background, I compiled and analyzed all the data used by the task force, presenting updates at our bi-weekly meetings over the 5-month life of the task force. With the retirement of the County’s General Registrar (director of elections for the county), I was asked to take over the 11-person office. While I declined the full time job offer, I did agree to be the Acting General Registrar for four months while the county conducted a search for a full time replacement. I have continued to be actively involved in election administration issues within the county since that time. I have continued to be involved with the county, now serving as chief judge in a number of rotating precincts that need assistance with each election, as well as serving on the County’s Historical Commission since 2015 (and elected Chairman twice since 2017).

III. U.S. CONGRESSIONAL REAPPORTIONMENT: BASELINE PROJECTIONS FOR 2020

14. For the past four decades I and Election Data Services have studied and issued yearly reports on the apportionment process using new population estimates released by the Census Bureau and private demographic firms. All our reports can be found at our website: www.electiondataservices.com, under the “Research” tab. We have become a staple for the press and others to cite when looking at the shift that is occurring in population between different states.

15. In the mid-1980s, E.D.S. Inc. developed software to calculate the distribution of congressional districts to the states based on population or other data. Initially developed in the Basic programming language, in the early 1990s, we reprogrammed it as macros for Excel spreadsheets. The program implemented the “method of equal proportions” formula that was adopted by the U.S. Congress in 1941 as the official manner to divide seats in the US House of Representatives among the states. As the Constitution stipulates, each state is provided at least one initial seat in the House of Representatives. The formula is actually used to apportion the remaining 385 districts. The formula works as follows:

The rest of the seats are handed out based on statistical “priority values” assigned to each additional seat that a state might get. In as close to plain English as the formula will allow, these priority values are calculated in a two-step process that requires dividing a state’s population by the square root of the product of the number of seats it’s already been assigned and that number plus one. The priority numbers are then rank ordered: “State A” will get an additional seat if its priority value for that seat is greater than any other state’s. The seats are disbursed to states based on these rankings until all 435 have been awarded.¹

¹ Greg Giroux, “Before Redistricting, That Other ‘R’ Word,” CQ Weekly (Nov. 30, 2009); *see also* Kristin D. Burnett, “Congressional Apportionment: 2010 Census Briefs,” U.S. Census Bureau (Nov. 2011), <https://www.census.gov/prod/cen2010/briefs/c2010br-08.pdf>.

16. Our reapportionment program calculates not only how many seats each state would receive based on the population or other numbers put into the formula, but it also calculates and reports the number of people a state gained its last seat by or lost the next seat by. It reports the last seat number that is given to a state, as well as what number seat the next district would be if the calculations continued past the 435 seat cut-off. The program also allows the user to change the maximum number of seats to be calculated. Finally, the program calculates the ideal district size for each state, by taking the state's total population and dividing it by the number of seats that the state has been awarded.

17. On at least a yearly basis, we have utilized the apportionment program to analyze the Census Bureau's annual state population estimates, which are usually released in late December each year. Our resulting studies and press releases have been consistently referenced by the media and scholars. Our studies are usually released the same day the Census Bureau estimates are unveiled and can be found on our website (www.electiondataservices.com). All of our historical studies (back to when we started them in 1994) and press releases are also kept on our website, available for all to see. The same tables have also been generated from the final decennial population numbers each decade back to 1940. Our website also has a historical table, that we have continued to update, showing the number of seats given to each state each decade back to the nation's founding in 1789.

18. We can utilize the annual estimates from the Bureau to create reliable projections of what the population, by state, might be at the time of the next decennial census (April 1 of the year ending in "0") and test those estimates on the anticipated deviations that will result. We do this projection each year and report the results in our press releases. A copy of our most recent study, released December 30, 2019, is attached to this report as **Exhibit 2**. For the purposes of studying the 2019 population estimates released by the Census Bureau in December 2019, E.D.S. Inc. created a series of estimates for possible 2020 population projections based upon

various amounts of change that were apparent in the Bureau's data. The three trend models used various time factors that the change would be calculated upon.

19. While our most recent study also reported on a "short-term change", a "mid-term change" and a "long-term change" model, at this point in the decade (when the Census is currently ongoing) it is logical to focus on just the "short-term change" model.

20. Using the 2019 population estimates, I am able to calculate a projected allocation of seats in the House of Representatives. I calculate the number of seats to be apportioned to each State based upon the so-called "method of equal proportions." As discussed above, under this formula, the population of each state is multiplied by a constant that is mathematically determined to test the priority of each state for an additional seat in the House. The only variable entered into the formula is the population of the states, as reported in the decennial Census. Any variation in the population will modify the priority ranking of the states and can cause a state to lose, or to fail to gain, an additional seat.

21. As we reported repeatedly in our 2019 report, and have continued to stress in press interviews, speeches, and conversations, the apportionment formula is very susceptible to slight changes in state's individual populations and how they relate to other states' populations. We always demonstrate this vulnerability by looking at the states that fall close to the magic 435 cut-off for seats.

2019 Reapportionment Analysis

2020 Projections (using 2018-2019 short-term trend)

| Last Five Seats | | Margin of Gain | Next Seats | | Margin of Loss |
|-----------------|------------------------------|----------------|------------|---------------------------------|----------------|
| 431 | Illinois (17 th) | 126,052 | 436 | Alabama (17 th) | 10,072 |
| 432 | New York (26 th) | 61,279 | 437 | Minnesota (8 th) | 21,992 |
| 433 | Texas (39 th) | 79,742 | 438 | Ohio (16 th) | 74,135 |
| 434 | Montana (2 nd) | 2,402 | 439 | California (53 rd) | 344,367 |
| 435 | Florida (29 th) | 44,285 | 440 | Rhode Island (2 nd) | 14,539 |

22. All of the above states are very possible to change their ranking, and therefore their allocation of seats, when the final population numbers are published at the end of this year.

23. We've seen this happen in past decades, as we always note in our studies, when circumstances like weather events have affected apportionment. The Census Bureau's estimated populations released for 2005 showed **Louisiana** would keep all their congressional districts that decade. Even the Bureau's own projections for 2010 released that same year showed **Louisiana** staying the same. Then hurricane Katrina hit **Louisiana** at the end of August 2005 (after the date of the population estimates). Devastation and population loss impacted New Orleans in a major way, and when the Bureau's 2006 population estimates were released **Louisiana** was looking at losing a congressional seat. That was ultimately confirmed when the 2010 Census was taken, and state data was released at the end of that year. Just last week, when Hurricane Laura came ashore in the Gulf Coast, I was called by several media and a Louisiana State Senator wondering about the likely impact on 2020. The current hurricane season, wild fires, and the ongoing COVID-19 pandemic make it more likely that undercounts will be exacerbated, particularly if Census operations are truncated.

24. A changed practice on how to count the military overseas could also change the final apportionment when it is announced December 31, 2020. For the 2020 Census the Census Bureau has changed the "residency rules" for counting the military by creating a distinction between personnel who are *deployed* overseas (usually for short periods of time) compared to those who are *stationed* or *assigned* overseas (frequently for longer periods of time). The Bureau will use DOD's administrative records to count *deployed* personnel at their usual residence in the US for both apportionment and redistricting purposes (they will be embedded within the state's resident population counts). On the other hand, personnel who are *stationed* or *assigned* overseas will be counted to their "home state of record" for apportionment purposes only and will show up as part of a state's total "overseas count" when the Bureau releases the final and

official apportionment data by December, 31, 2020. Military sources have told the Census Bureau that of all overseas military, approximately 15% are *deployed* personnel and 85% are *stationed* or *assigned* overseas. Overseas military personnel have been a factor in the apportionment formula for the past several decades, including the switching of the final district in 2000 that went from **Utah** to **North Carolina**.

25. These numbers are likely to also be significantly impacted by how well the Commerce Department and Census Bureau conducts the census, how well the American public responds to this decennial exercise, the first Census where major components will be conducted via the internet, and whether the discussion on a Census citizenship question over the past year will cause some groups to avoid participating. With these complications and policies described above, the truncation of the 2020 Census field operations and post-processing is likely to prevent enumeration of people in hard to count communities and increase the differential undercount.

26. As I noted in EDS's report from last year's we cautioned users that even though there is a very short time before the Census, the population projections are still subject to change. "We are now at a place where the rubber meets the road," I said. "How well does the Census Bureau and the Trump administration put on the greatest mobilization of government resources outside of war time? How well will the public respond and answer the Census, given the competing focuses of everyday life and the need to utilize the internet? Will the fear of foreign intervention also impact the census?" I noted. "Having worked with Census data and estimates since the 1970s, it is important to remember that major events like Katrina and the 2008 recession each changed population growth patterns and that impacted and changed the next apportionment," I said.

27. The ore apparent with the low response rates still being identified across the country. Because the Census Bureau has had to react to the pandemic that appeared right when the counting process was beginning, they initially requested a delay of four months in the reporting

requirements in proposed language to Congress. Yet, in the last month the Trump administration has pulled back that delay, and instead reinstituted the original reporting requirements of December 31, 2020 for the apportionment numbers. As a result, the Bureau has shortened the time to find people who have not responded to the census, thinned down the time to process the census questionnaires, and cut various procedural processes to check whether the counting process is correct.

28. Just this morning, the Bureau's website was showing a nationwide response rate of just 64.9% as of Saturday evening, August 29th, 2020, their latest estimates. Additionally, they note another 16.9% have been enumerated in the follow-up procedure called Non-Response Follow Up (NRFU), for a total nationwide enumerated rate of 81.7%.

29. But these "enumerated rates" vary greatly by state. Idaho is currently at the highest rate of 96.5%, helped greatly from the 27.8% that were found in the NRFU program. The state of New Mexico is at the bottom of the list, showing a self-response rate of 55.6%, an enumerated in Nonresponse rate of 15.6%, and a total enumerated rate of 71.2%.

30. Looking at four of the five states where the last five seats are expected to be allocated, those states are also all below the average self-response rate for the nation, which is 64.9 % as of August 29, 2020. For example, New York has a self-response rate of 61.0 %, Florida has a self-response rate of 61.5%, and Texas has a self-response rate of 60.2%. If the final population counts of these three states, that are currently projected to gain one of the last congressional seats, are undercounted, by even tens of thousands of people, those states will lose a congressional seat to a different state.

31. **Exhibit 3** in this report is a table of these response rates reported this morning where I have sorted the states by the overall enumerated rates. At the bottom of the list are the mostly southern states of New Mexico, Georgia, Puerto Rico, Arizona, Alabama, Montana, South Carolina, Mississippi, North Carolina, Louisiana, Florida and Texas (listed in order of least

enumerated rate to higher). Except for Montana, all of these listed states have higher than average concentration of minority racial groups in their population.

32. Clearly minority racial groups are being negatively affected disproportionately by the challenges of this Census. When one uses the Bureau's same reporting system to look down at the tract level, one can find the lowest self-response rates in areas heavily populated by African-Americans (including inner cities), Hispanics (including colonias), and Native America communities (reservations). On the other hand, the best self-response rates are in suburban communities. Unfortunately, the Bureau does not report the NRFU numbers at the tract level, so it is unknown whether that process is successful or not.

33. The Bureau's changes to the timeline for the counting and post-count process will likely result in a greater undercount than experienced in prior censuses. Based on my experience and knowledge, this will likely have a significant effect on the accuracy of the census, meaning more individuals will be missed in certain underperforming states and in hard to count communities. There is also a strong potential to impact a number of states in the apportionment process if the period for counting and post-processing is truncated to September 30. Furthermore, states use Census data in their state legislative redistricting processes, and undercounts of hard to count communities can result in the loss of state and local legislative seats for the undercounted areas.

I declare under penalty of perjury that the foregoing is true and correct.

A handwritten signature in black ink, reading "Kimball W. Brace". The signature is fluid and cursive, with the first name "Kimball" being more prominent and the last name "Brace" following in a similar style.

Kimball W. Brace

Executed on August 31, 2020 at Manassas, Virginia.

APPENDIX 1

(Exhibit 1 to Declaration of Kimball W. Brace)

VITA

KIMBALL WILLIAM BRACE

Election Data Services, Inc.
6171 Emerywood Court
Manassas, VA 20112-3078

703 580-7267 or 202 789-2004 phone
703 580-6258 fax

kbrace@electiondataservices.com or kbrace@aol.com

Kimball Brace is the president of Election Data Services Inc., a consulting firm that specializes in redistricting, election administration, and the analysis and presentation of census and political data. Mr. Brace graduated from the American University in Washington, D.C., (B.A., Political Science) in 1974 and founded Election Data Services in 1977.

Redistricting Consulting

Activities include software development; construction of geographic, demographic, or election databases; development and analysis of alternative redistricting plans; general consulting, and onsite technical assistance with redistricting operations.

Congressional and Legislative Redistricting

Arizona Independent Redistricting Commission: Election database, 2001

Arizona Legislature, Legislative Council: Election database, 2001

Colorado General Assembly, Legislative Council: Geographic, demographic, and election databases, 1990–91

Connecticut General Assembly

- Joint Committee on Legislative Management: Election database, 2001; and software, databases, general consulting, and onsite technical assistance, 1990–91
- Senate and House Democratic Caucuses: Demographic database and consulting, 2001

Florida Legislature, House of Rep.: Geographic, demographic, and election databases, 1989–92

Illinois General Assembly

- Speaker of House and Senate Minority Leader: Software, databases, general consulting, and onsite technical assistance, 2000–02,
- Speaker of House and President of Senate: Software, databases, general consulting, and onsite technical assistance, 2018-current, 2009-2012, 1990–92, and 1981-82

Iowa General Assembly, Legislative Service Bureau and Legislative Council: Software, databases, general consulting, and onsite technical assistance, 2000–01 and 1990–91

Kansas Legislature: Databases and plan development (state senate and house districts), 1989

Massachusetts General Court

- Senate Democratic caucus: Election database and general consulting, 2001–02
- Joint Reapportionment Committees: Databases and plan development (cong., state senate, and state house districts), 1991–93, 2010-2012

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(Redistricting Consulting, cont.)

Michigan Legislature: Geographic, demographic, and election databases, 1990–92; databases and plan development (cong., state senate, and state house districts), 1981–82

Missouri Redistricting Commission: General consulting, 1991–92

Commonwealth of Pennsylvania: General consulting, 1992

Rhode Island General Assembly and Reapportionment Commissions

- Software, databases, plan development, and onsite assistance (cong., state senate, and state house districts), 2016– current, 2010–2012, 2001–02 and 1991–92
- Databases and plan development (state senate districts), 1982–83

State of South Carolina: Plan development and analysis (senate), U.S. Dept. of Justice, 1983–84

Local Government Redistricting

Orange County, Calif.: Plan development (county board), 1991–92

City of Bridgeport, Conn.: Databases and plan development (city council), 2011–2012 and 2002–03

Cook County, Ill.: Software, databases, and general consulting (county board), 2010–2012, 2001–02, 1992–1993, and 1989

Lake County, Ill.: Databases and plan development (county board), 2011 and 1981

City of Chicago, Ill.: Software, databases, general consulting, and onsite technical assistance (city wards), 2010–2012, 2001–02 and 1991–92

City of North Chicago, Ill.: Databases and plan development (city council), 1991 and 1983

City of Annapolis, Md.: Databases and plan development (city council), 1984

City of Boston, Mass.: Databases and plan development (city council), 2011–2012, 2001–2002, and 1993

City of New Rochelle, N.Y.: Databases and plan development (city council), 1991–92

City of New York, N.Y.: Databases and plan development (city council), 1990–91

Cities of Pawtucket, Providence, East Providence, and Warwick, and town of North Providence, R.I.: Databases and plan development (city wards and voting districts), 2011–2012, 2002

City of Woonsocket and towns of Charlestown, Johnston, Lincoln, Scituate and Westerly, R.I.: Databases and plan development (voting districts), 2011–2012, 2002; also Westerly 1993

City of Houston, Tex.: Databases and plan development (city council), 1979 — recommended by U.S. Department of Justice

City of Norfolk, Va.: Databases and plan development (city council), 1983–84 — for Lawyers' Committee for Civil Rights

Virginia Beach, Va.: Databases and plan development (city council), 2011–2012, 2001–02, 1995, and 1993

Other Activities

International Foundation for Electoral Systems (IFES) and U.S. Department of State: redistricting seminar, Almaty, Kazakhstan, 1995

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Library of Congress, Congressional Research Service: Consulting on reapportionment, redistricting, voting behavior and election administration

National Conference of State Legislatures (NCSL): Numerous presentations on variety of redistricting and election administration topics, 1980 - current

Election Administration Consulting

Activities include seminars on election administration topics and studies on voting behavior, voting equipment, and voter registration systems.

Prince William County, VA:

2013 – Appointed by Board of County Supervisors to 15 member Task Force on Long Lines following 2012 election. Asked and appointed by County's Electoral Board to be Acting General Registrar for 5-month period between full-time Registrars.

2008 - current – poll worker and now chief judge for various precincts in county

U.S. Election Assistance Commission (EAC): Served as subcontractor to prime contractors who compiled survey results from 2008 and 2010 Election Administration and Voting Survey.

U.S. Election Assistance Commission (EAC): Compile, analyze, and report the results of a survey distributed to state election directors during FY–2007. Survey results were presented in the following reports of the EAC: *The Impact of the National Voter Registration Act of 1993 on the Administration of Elections for Federal Office, 2005–2006, A Report to the 110th Congress*, June 30, 2007; *Uniformed and Overseas Citizens Absentee Voting Act (UOCAVA), Survey Report Findings*, September, 2007; and *The 2006 Election Administration and Voting Survey, A Summary of Key Findings*, December, 2007.

U.S. Election Assistance Commission (EAC): Compile, analyze, and report the results of three surveys distributed to state election directors during FY–2005: Election Day, Military and Overseas Absentee Ballot (UOCAVA), and Voter Registration (NVRA) Surveys. Survey results were presented in the following reports: *Final Report of the 2004 Election Day Survey*, by Kimball W. Brace and Dr. Michael P. McDonald, September 27, 2005; and *Impact of the National Voter Registration Act of 1993 on the Administration of Elections for Federal Office, 2003–2004, A Report to the 109th Congress*, June 30, 2005.

Rhode Island Secretary of State: Verification of precinct and district assignment codes in municipal registered voter files and production of street files for a statewide voter registration database, on-going maintenance of street file, 2004-2006, 2008-2014, 2016-2017.

Rhode Island Secretary of State, State Board of Elections & all cities & towns: production of precinct maps statewide, 2012, 2002, 1992

District of Columbia, Board of Elections and Ethics (DCBOEE): Verification of election ward, Advisory Neighborhood Commission (ANC), and Single-Member District (SMD) boundaries and production of a new street locator, 2003. Similar project, 1993.

Harris County, Tex.: Analysis of census demographics to identify precincts with language minority populations requiring bilingual assistance, 2002–03

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(Election Administration Consulting, cont.)

Cook County, Ill., Election Department and Chicago Board of Election Commissioners:

- Analysis of census demographics to identify precincts with language minority populations requiring bilingual assistance, 2019, 2010-2013, 2002-03
- Study on voting equipment usage and evaluation of punch card voting system, 1997

Chicago Board of Election Commissioners: Worked with Executive Director & staff in Mapping Dept. to redraw citywide precincts, eliminate over 600 to save costs, 2011-12

Library of Congress, Congressional Research Service: Nationwide, biannual studies on voter registration and turnout rates, 1978-2002

U.S. General Accounting Office (GAO), U.S. Dept. of Justice, and numerous voting equipment vendors and media: Data on voting equipment usage throughout the United States, 1980-present

Needs assessments and systems requirement analyses for the development of statewide voter registration systems:

- Illinois State Board of Elections: 1997
- North Carolina State Board of Elections, 1995
- Secretary of Commonwealth of Pennsylvania, 1996

Federal Election Commission, Office of Election Administration:

- Study on integrating local voter registration databases into statewide systems, 1995
- Nationwide workshops on election administration topics, 1979-80
- Study on use of statistics by local election offices, 1978-79

Cuyahoga County, Ohio, Board of Elections: Feasibility study on voting equipment, 1979

Winograd Commission, Democratic National Committee: Analysis of voting patterns, voter registration and turnout rates, and campaign expenditures from 1976 primary elections

Mapping and GIS

Activities include mapping and GIS software development (geographic information systems) for election administration and updating TIGER/Line files for the decennial census.

2000 Census Transportation Planning Package (CTPP), 1998-99: GIS software for the U.S. Department of Transportation to distribute to 400 metropolitan planning organizations (MPOs) and state transportation departments for mapping traffic analysis zones (TAZs) for the 2000 census; provided technical software support to MPOs

Census 2000, 2010 and 2020 Redistricting Data Program, Block Boundary Suggestion Project (Phase 1) and Voting District Project (Phase 2), 1995-99: GIS software and provided software, databases, and technical software support to the following program participants:

- Alaska Department of Labor
- Connecticut Joint Committee on Legislative Management
- Illinois State Board of Elections
- Indiana Legislative Services Agency
- Iowa Legislative Service Bureau

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(Mapping & GIS Support, cont.)

- New Mexico Legislative Council Service
- Rhode Island General Assembly
- Virginia Division of Legislative Services

Developed PRECIS[®] Precinct Information System—GIS software to delineate voting precinct boundaries—and delivered software, databases, and technical software support to the following state and local election organizations (with date of installation):

- Cook County, Ill., Department of Elections (1993)
- Marion County, Fla., Supervisor of Elections (1995)
- Berks County Clerk, Penn. (1995)
- Hamilton County, Ohio, Board of Elections (1997)
- Brevard County, Fla., Supervisor of Elections (1999)
- Osceola County, Fla., Supervisor of Elections (1999)
- Multnomah County, Ore, Elections Division (1999)
- Chatham County, Ga., Board of Elections (2000)
- City of Chicago, Ill., Board of Election Commissioners (2000)
- Mahoning County, Ohio, Board of Elections (2000)
- Iowa Secretary of State, Election and Voter Registrations Divisions (2001)
- Woodbury County, Iowa, Elections Department (2001)
- Franklin County, Ohio, Board of Elections (2001)
- Cobb County, Ga., Board of Elections and Voter Registration (2002)

Illinois State Board of Elections, Chicago Board of Election Commissioners, and Cook County Election Department: Detailed maps of congressional, legislative, judicial districts, 1992

Associated Press: Development of election night mapping system, 1994

Litigation Support

Activities include data analysis, preparation of court documents and expert witness testimony. Areas of expertise include the census, demographic databases, district compactness and contiguity, racial bloc voting, communities of interest, and voting systems. Redistricting litigation activities also include database construction and the preparation of substitute plans.

State of Alabama vs. US Department of Commerce, et al (2019-2020) apportionment & citizenship data

NAACP vs. Denise Merrill, CT Secretary of State, et al (2019-2020) state legislative redistricting and prisoner populations

Latasha Holloway, et al. v. City of Virginia Beach, VA (2019) city council redistricting

Joseph V. Aguirre vs. City of Placentia, CA (2018-2019), city council redistricting

Davidson, et al & ACLU of Rhode Island vs. City of Cranston, RI (2014-16), city council & school committee redistricting with prisoner populations.

Navaho Nation v. San Juan County, UT (2014-17) county commissioner & school board districts.

Michael Puyana vs. State of Rhode Island (2012) state legislature redistricting

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(Litigation Support, cont.)

United States of America v. Osceola County, Florida, (2006), county commissioner districts.

Deeds vs McDonnell (2005), Va. Attorney General Recount

Indiana Democratic Party, et al., v. Todd Rokita, et al. (2005), voter identification.

Linda Shade v. Maryland State Board of Elections (2004), electronic voting systems

Gongaley v. City of Aurora, Ill. (2003), city council districts

State of Indiana v. Sadler (2003), ballot design (city of Indianapolis-Marion County, Ind.)

Peterson v. Borst (2002–03), city-council districts (city of Indianapolis-Marion County, Ind.)

New Rochelle Voter Defense Fund v. City of New Rochelle, City Council of New Rochelle, and Westchester County Board Of Elections (2003), city council districts (New York)

Charles Daniels and Eric Torres v. City of Milwaukee Common Council (2003), council districts (Wisconsin)

The Louisiana House of Representatives v. Ashcroft (2002–03), state house districts

Camacho v. Galvin and Black Political Caucus v. Galvin (2002–03), state house districts (Massachusetts)

Latino Voting Rights Committee of Rhode Island, et al., v. Edward S. Inman, III, et al. (2002–03), state senate districts

Metts, v. Harmon, Almond, and Harwood, et al. (2002–03), state senate districts (Rhode Island)

Joseph F. Parella, et al. v. William Irons, et al. (2002–03), state senate districts (Rhode Island)

Jackson v. County of Kankakee (2001–02), county commissioner districts (Illinois)

Corbett, et al., v. Sullivan, et al. (2002), commissioner districts (St Louis County, Missouri)

Harold Frank, et al., v. Forest County, et al. (2001–02), county commissioner districts (Wisc.)

Albert Gore, Jr., et al., v. Katherine Harris as Secretary of State, State of Florida, et al., and The Miami Dade County Canvassing Board, et al., and The Nassau County Canvassing Board, et al., and The Palm Beach County Canvassing Board, et al., and George W. Bush, et al (2000), voting equipment design — Leon County, Fla., Circuit Court hearing, December 2, 2000, on disputed ballots in Broward, Volusia, Miami-Dade, and Palm Beach counties from the November 7, 2000, presidential election.

Barnett v. Daley/PACI v. Daley/Bonilla v. Chicago City Council (1992–98), city wards

Donald Moon, et al. v. M. Bruce Meadows, etc and Curtis W. Harris, et al. (1996–98), congressional districts (Virginia)

Melvin R. Simpson, et al. v. City of Hampton, et al. (1996–97), city council districts (Va.)

Vera vs. Bush (1996), Texas redistricting

In the Matter of the Redistricting of Shawnee County Kansas and Kingman, et al. v. Board of County Commissioners of Shawnee County, Kansas (1996), commissioner districts

Vecinos de Barrio Uno v. City of Holyoke (1992–96), city council districts (Massachusetts)

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(Litigation Support, cont.)

Torres v. Cuomo (1992–95), congressional districts (New York)
DeGrandy v. Wetherell (1992–94), congressional, senate, and house districts (Florida)
Johnson v. Miller (1994), congressional districts (Georgia)
Jackson, et al v Nassau County Board of Supervisors (1993), form of government (N.Y.)
Gonzalez v. Monterey County, California (1992), county board districts
LaPaille v. Illinois Legislative Redistricting Commission (1992), senate and house districts
Black Political Task Force v. Connolly (1992), senate and house districts (Massachusetts)
Nash v. Blunt (1992), house districts (Missouri)
Fund for Accurate and Informed Representation v. Weprin (1992), assembly districts (N.Y.)
Mellow v. Mitchell (1992), congressional districts (Pennsylvania)
Phillip Langsdon v. Milsaps (1992), house districts (Tennessee)
Smith v. Board of Supervisors of Brunswick County (1992), supervisor districts (Virginia)
People of the State of Illinois ex. rel. Burris v. Ryan (1991–92), senate and house districts
Good v. Austin (1991–92), congressional districts (Michigan)
Neff v. Austin (1991–92), senate and house districts (Michigan)
Hastert v. Illinois State Board of Elections (1991), congressional districts
Republican Party of Virginia et al. v. Wilder (1991), senate and house districts
Jamerson et al. v. Anderson (1991), senate districts (Virginia)
Ralph Brown v. Iowa Legislative Services Bureau (1991), redistricting database access
Williams, et al. v. State Board of Election (1989), judicial districts (Cook County, Ill.)
Fifth Ward Precinct 1A Coalition and Progressive Association v. Jefferson Parish School Board (1988–89), school board districts (Louisiana)
Michael V. Roberts v. Jerry Wamser (1987–89), St. Louis, Mo., voting equipment
Brown v. Board of Commissioners of the City of Chattanooga, Tenn. (1988), county commissioner districts
Business Records Corporation v. Ransom F. Shoup & Co., Inc. (1988), voting equip. patent
East Jefferson Coalition for Leadership v. The Parish of Jefferson (1987–88), parish council districts (Louisiana)
Buckanaga v. Sisseton School District (1987–88), school board districts (South Dakota)
Griffin v. City of Providence (1986–87), city council districts (Rhode Island)
United States of America v. City of Los Angeles (1986), city council districts
Latino Political Action Committee v. City of Boston (1984–85), city council districts
Ketchum v. Byrne (1982–85), city council districts (Chicago, Ill.)

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(Litigation Support, cont.)

State of South Carolina v. United States (1983–84), senate districts — U.S. Dept. of Justice

Collins v. City of Norfolk (1983–84), city council districts (Virginia) — for Lawyers' Committee for Civil Rights

Rybicki v. State Board of Elections (1981–83), senate and house districts (Illinois)

Licht v. State of Rhode Island (1982–83), senate districts (Rhode Island)

Agerstrand v. Austin (1982), congressional districts (Michigan)

Farnum v. State of Rhode Island (1982), senate districts (Rhode Island)

In Re Illinois Congressional District Reapportionment Cases (1981), congressional districts

Publications

"EAC Survey Sheds Light on Election Administration", *Roll Call*, October 27, 2005 (with Michael McDonald)

Developing a Statewide Voter Registration Database: Procedures, Alternatives, and General Models, by Kimball W. Brace and M. Glenn Newkirk, edited by William Kimberling, (Washington, D.C.: Federal Election Commission, Office of Election Administration, Autumn 1997).

The Election Data Book: A Statistical Portrait of Voting in America, 1992, Kimball W. Brace, ed., (Bernan Press, 1993)

"Geographic Compactness and Redistricting: Have We Gone Too Far?", presented to Midwestern Political Science Association, April 1993 (with D. Chapin and R. Niemi)

"Whose Data is it Anyway: Conflicts between Freedom of Information and Trade Secret Protection in Redistricting", *Stetson University Law Review*, Spring 1992 (with D. Chapin and W. Arden)

"Numbers, Colors, and Shapes in Redistricting," *State Government News*, December 1991 (with D. Chapin)

"Redistricting Roulette," *Campaigns and Elections*, March 1991 (with D. Chapin)

"Redistricting Guidelines: A Summary", presented to the Reapportionment Task Force, National Conference on State Legislatures, November 9, 1990 (with D. Chapin and J. Waliszewski)

"The 65 Percent Rule in Legislative Districting for Racial Minorities: The Mathematics of Minority Voting Equality," *Law and Policy*, January 1988 (with B. Grofman, L. Handley, and R. Niemi)

"Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" *Journal of Politics*, February 1987 (with B. Grofman and L. Handley)

"New Census Tools," *American Demographics*, July/August 1980

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Professional Activities

Member, Task Force on Long Lines in 2012 Election, Prince William County, VA

Member, 2010 Census Advisory Committee, a 20-member panel advising the Director of the Census on the planning and administration of the 2010 census.

Delegate, Second Trilateral Conference on Electoral Systems (Canada, Mexico, and United States), Ontario, Canada, 1995; and Third Trilateral Conference on Electoral Systems, Washington, D.C., 1996

Member, American Association of Political Consultants

Member, American Association for Public Opinion Research

Member, American Political Science Association

Member, Association of American Geographers, Census Advisory Committee

Member Board of Directors, Association of Public Data Users

Member, National Center for Policy Alternatives, Voter Participation Advisory Committee

Member, Urban and Regional Information Systems Association

Historical Activities

Member, Manassas Battlefield Trust Board Member, 2018 -- current

Member, Historical Commission, Prince William County, VA., 2015 – current. Elected Chairman in 2017, re-elected 2018

Member of Executive Committee & head of GIS Committee, Bull Run Civil War Round Table, Centerville, VA. 2015 – current

Member, Washington Capitals Fan Club, Executive Board 2017 -- current

February, 2020

APPENDIX 2

(Exhibit 2 to Declaration of Kimball W. Brace)



6171 Emerywood Court
Manassas, Virginia 20112

202 789.2004 tel. or
703 580.7267
703 580.6258 fax
Info@electiondataservices.com

FOR IMMEDIATE RELEASE

Date: December 30, 2019
Contact: Kimball W. Brace
Tel.: (202) 789-2004 or (703) 580-7267
Email: kbrace@electiondataservices.com
Website: www.electiondataservices.com

Montana Gains California's Seat With New 2019 Census Estimates; But Alabama & Ohio to also lose by 2020

New Census Bureau population estimates for 2019 released today shows a change of one more seat between two states from last year's study generated by Election Data Services, Inc. on which states would gain or lose congressional seats if the current estimate numbers were used for apportionment in 2019. But projecting these numbers to 2020, using several different methods, leads to more states being impacted by the decennial census scheduled to take place in just four months. These numbers could also be majorly impacted by how well the Commerce Department and Census Bureau conducts the census, how well the American public responds to this decennial exercise, the first where major components will be conducted via the internet, and whether the discussion on citizenship over the past year will cause some groups to avoid participating. A changed practice on how to count the military overseas could also change the final apportionment when it is announced December 31, 2020.

The Bureau's 2019 total population estimates show that now 15 states will be impacted by changes in their congressional delegation if these new numbers were used for apportionment today. The state of **Montana** joins the previously indicated states of **Arizona, Colorado, Florida, North Carolina, and Oregon** to each gain a single seat while the state of **Texas** is now shown to gain a second seat with the new data. The state of **California** joins the states of **Illinois, Michigan, Minnesota, New York, Pennsylvania, Rhode Island, and West Virginia** to lose a seat in Congress using the new data. A map of the 2019 numbers is attached.

The new numbers, however, reflect subtle changes taking place across the nation in birth and death rates and resulting total population numbers that become magnified when the information is projected forward to coincide with the taking of the Census on April 1, 2020. Election Data Services created a variety of different methodologies to project the 2019 data forward nine months (from the July 1, 2019 date of the Census estimates) to April 1, 2020 (several short-term projection methods for the trend occurring in 2018-2019, and 2017-2019, a middle term

"Experts in Elections"  "Redistricting & GIS"

methodology using the 2015-2019 trend, and a long-term projection for 2011-2019). The different methodologies benefit some states and disadvantage others in the "musical-chairs" effort of allocating 435 seats to the 50 states. All the methods would add a second seat for **Florida** and a third seat for **Texas**, to the list of states noted above that will gain one or more seats by 2020. The list of losing states will expand to also include **Alabama** and **Ohio**, by the time the Census is taken in 2020. A map showing the 2020 projected apportionment using the 2018-2019 trend is attached. Because all the projection models produce the same state overall results in seats as the 2018-2019 trend map, only the tables of the calculations for the different projection models are attached so that how close states are to changes can be observed.

The new 2019 data and all projections forward to 2020 now confirms that **California** will lose a congressional district in 2020. Our 2018 study first picked up the possibility that **California** could lose a congressional district for the first time in their nearly 160-year history. The new 2019 numbers from the Bureau indicate the state would lose that seat by 98,709 people but projecting the data forward to 2020 shows the state further away from potentially keeping that seat, losing it by over 300,000 people in 2020.

While the 2019 Census estimate numbers show **Alabama** keeping their seventh seat by a slim margin of just 18,516 people, projecting the data forward to 2020 would find the state losing the seventh seat by only 10,072 to 19,074 people, depending on the projection model utilized. All of the projection models find **Alabama** just missing the last seat to be apportioned, coming in at seat #436 when there are only 435 seats to hand out (a cut-off mark established in 1910).

The state of **Montana** is just barely able to reverse previous decades of population shifts when it went from two seats down to one in 1990. For 2020 the state is projected to go back to having two seats, but that gain of a second seat is because the state occupies the dubious distinction of obtaining seat #435, the last one to be apportioned. Election Data Services calculations show **Montana** getting that additional seat by only between 2,402 and 4,163 people to spare; a very close margin.

Rhode Island is also a state with an extremely close margin. For most of the decade our studies have projected that **Rhode Island** would lose their second seat by the end of the decade and the new numbers confirm that projection. But their margin has gotten tighter with the new data. For the past several years we saw that **Rhode Island** would lose that second seat by more than 25,000 people. But this new data shows the state missing the seat by only 14,539 residents.

Previous Election Data Services studies have hinted that the states of **Illinois** and **New York** might be in a position to each lose a second seat by 2020. However, these new Census numbers seem to indicate this will not be the case, with both states just losing a single seat each.

The state of **Minnesota** is also close to the margin of likely losing a seat in Congress. All of the projections place the state at position #437, having lost their last seat (their 8th) by between 6,740 people (the 2019 estimate) to around 21,000 people. **Minnesota**'s state demographer has indicated that recent influx of people to the state has boosted their numbers and it is likely to have had an impact on reapportionment.

Using any methodology, the population projections points toward a ten (10) seat change over 17 states across the nation by year 2020. States that will gain single seats include **Arizona, Colorado, Montana, North Carolina, and Oregon**, while **Florida** is set to gain two congressional districts and **Texas** would gain three seats. Single seat losses will again occur in the Midwest and Northeast sections of the nation, where **Alabama, California, Illinois, Michigan, Minnesota, New York, Ohio, Pennsylvania, Rhode Island** and **West Virginia** would each lose a seat. All other states would keep the same number of representatives they were awarded in December 2010 when the official 2010 Census numbers were released.

In table form, the gainers and losers are:

| States Gaining Districts (7) | States Losing Districts (10) |
|--|--|
| Arizona +1 (from 9 to 10) | Alabama -1 (from 7 to 6) |
| Colorado +1 (from 7 to 8) | California -1 (from 53 to 52) |
| Florida +2 (from 27 to 29) | Illinois -1 (from 18 to 17) |
| Montana +1 (from At-large to 2) | Michigan -1 (from 14 to 13) |
| North Carolina +1 (from 13 to 14) | Minnesota -1 (from 8 to 7) |
| Oregon +1 (from 5 to 6) | New York -1 (from 27 to 26) |
| Texas +3 (from 36 to 39) | Ohio -1 (from 16 to 15) |
| | Pennsylvania -1 (from 18 to 17) |
| | Rhode Island -1 (from 2 to 1) |
| | West Virginia -1 (from 3 to 2) |

With only four months until Census Day, many states have appropriated funds to help send a message to their constituents about the importance of participating in the Censusⁱ. Many of these states are on the edge of gaining or losing a seat in the apportionment process, but there are some notable exceptions. For example, Texas has not appropriated any funds for Complete Count efforts, and yet whether they stand to gain only two or maybe three additional seats may depend on how good the counting is conducted in the state. This could also be impacted by the reaction to the citizenship issue that has become more of a focus in the past year. Florida has also failed to appropriate any funds for Complete Count efforts in 2020, but they are more firm in the projection of receiving two additional seats in 2020. Thus, the two largest gaining states in number of seats are those that didn't spend their own money to help the counting process.

Since 1941, by law the number of seats in the U.S. House of Representatives has been capped at 435. As a result, there has always been interest in finding which states are close to that magic bubble, either just gaining their last seat, or just missing their next seat. The following table shows the results of the 2019 population estimates, as well as one of the short-term trend methodology calculations (2018-2019) for the seats within five positions of the 435 cut off.

| 2019 Reapportionment Analysis | | | |
|--------------------------------------|-----------------------|---|-----------------------|
| 2019 Population Estimates | | 2020 Projections (using 2018-2019 short-term trend) | |
| Last Five Seats | Margin of Gain | Last Five Seats | Margin of Gain |
| 431 Arizona (10th) | 128,294 | 431 Illinois (17 th) | 126,052 |
| 432 New York (26th) | 237,376 | 432 New York (26 th) | 61,279 |
| 433 Alabama(7th) | 18,516 | 433 Texas (39 th) | 79,742 |
| 434 Montana (2 nd) | 2,856 | 434 Montana (2 nd) | 2,402 |
| 435 Ohio (16 th) | 12,508 | 435 Florida (29th) | 44,285 |

| 2019 Reapportionment Analysis | | | |
|--------------------------------------|-----------------------|---|-----------------------|
| 2019 Population Estimates | | 2020 Projections (using 2018-2019 short-term trend) | |
| Next Seats | Margin of Loss | Next Seats | Margin of Loss |
| 436 Florida (29 th) | 23,006 | 436 Alabama (7th) | 10,072 |
| 437 Minnesota (8th) | 6,740 | 437 Minnesota (8th)) | 21,992 |
| 438 Texas (39th) | 51,004 | 438 Ohio (16th) | 74,135 |
| 439 California (53 rd) | 98,709 | 439 California (53rd) | 344,367 |
| 440 Rhode Island (2 nd) | 7,703 | 440 Rhode Island (2 nd) | 14,539 |

The Census Bureau's yearly release of population estimates also results in a revision of previous year estimates. While Election Data Services has traditionally reflected those revisions in our projection methodology, we have created a new apportionment table that shows the apportionment results for each year in the decade based upon those revised numbers. The table, entitled "2020 Apportionment Calculations based on different trend lines coming from the 2019 Census Bureau Estimates" is attached to this press release. The table shows consistent gains and losses of seats over the entire decade with the new data. The table also includes a chart of where seats # 430 through # 440 would be assigned to states in each projection.

Kimball Brace, President of Election Data Services, Inc. cautioned users that even though there is a very short time before the Census, the population projections are still subject to change. "We are now at a place where the rubber meets the road. How well does the Census Bureau and the Trump administration put on the greatest mobilization of government resources outside of war time? How well will the public respond and answer the Census, given the competing focuses of everyday life and the need to utilize the internet? Will the fear of foreign intervention also impact the census?" Brace noted. "Having worked with Census data and estimates since the 1970s, it is important to remember that major events like Katrina and the 2008 recession each changed population growth patterns and that impacted and changed the next apportionment," he said.

Brace also noted that major changes in the counting process are in the works for 2020 and that reduced budget funding could impact those plans. "History can also be a guide, recalling that the 1920 apportionment was cancelled because the numbers showed for the first time that more people resided in urban areas than rural areas" said Brace. "I have had my share of nightmares that a failed Census process could lead to unreliable numbers and a repeat of 1920."

Because congressional apportionment also impacts the Electoral College and the vote for President, Election Data Services took the 2020 projections for each state and applied the Presidential election results from the past five Presidential contests to determine the Electoral College outcomes in the past 16 years. The study shows that none of the presidential contests would have elected a different presidential candidate using the new apportionment counts but they would have been more Republican in nature. For example, in 2016 President Trump would have gained two additional electoral college votes under the new apportionment projections. In 2012 President Obama would still have won the Electoral College, but with four less votes (328 vs 332) than he won at the time of the voting. The biggest change would have occurred in the 2000 presidential election where George Bush would have gained an additional 20 electoral votes had the new 2020 apportionment projections determined the number of congressional seats in each state.

The 2016 Electoral College was muddled because 7 electors voted for a different candidate than what they had pledged based on the vote totals. As a result, the overall change in candidate votes based on the new apportionment numbers shows just two vote difference in the bottom line results. President elect Trump's ability to carry states that will be losing congressional seats in 2020 also contributed to a reversal of the pattern depicted in previous elections.

It should be noted that the 2020 Presidential election and resulting Electoral College will occur before the results of the 2020 Census are released by December 31, 2020. Therefore, the Electoral College results in 2020 will be governed by the state's apportionment allocation as they exist today, having been first determined in 2011. The first time the new 2020 apportionment results will be utilized will be the 2024 Presidential election. Election Data Services, Inc. has also worked with the website [270ToWin](#), who has built an interactive map of the these new apportionment results where users can adjust state outcomes to discover Electoral College outcomes for the presidential elections back to 2000.

Major weather events have also affected apportionment. The Census Bureau's estimated populations released for 2005 showed **Louisiana** would keep all their congressional districts that decade. Even the Bureau's own projections for 2010 released that same year showed **Louisiana** staying the same. Then hurricane Katrina hit **Louisiana** at the end of August 2005 (after the date of the population estimates). Devastation and population loss impacted New Orleans in a major way, and when the Bureau's 2006 population estimates were released **Louisiana** was looking at losing a congressional seat. That was ultimately confirmed when the 2010 Census was taken, and state data was released at the end of that year.

As Election Data Services, Inc. noted last year in the 2017 study, the year of 2017 saw 18 hurricanes and tropical storms, three of which had a potential of impact on population movements in the United States. Two of these storms: Irma (impacting Miami and the Florida Gulf Coast), and Maria (which devastated Puerto Rico)) affected **Florida** and the new population estimates reflect that fact. Last years study showed **Florida** was 366,735 people away from gaining a third seat.

The 2019 data shows the state is only 172,169 people away from a third additional seat, an improvement of nearly 200,000 people.

The 2019 population estimates have not been statistically adjusted for any known undercount that may take place when the Census is conducted. In addition, no estimates were provided for U.S. military personnel overseas. This component has in the past been counted by the Census Bureau and allocated to the states based on administrative records retained by the military. Overseas military personnel have been a factor in the apportionment formula for the past several decades, including the switching of the final district in 2000 that went from **Utah** to **North Carolina**.

For 2020 the Census Bureau has changed the “residency rules” for counting the military by creating a distinction between personnel who are *deployed* overseas (usually for short periods of time) compared to those who are *stationed* or *assigned* overseas (frequently for longer periods of time). The Bureau will use DOD’s administrative records to count *deployed* personnel at their usual residence in the US for both apportionment and redistricting purposes (they will be embedded within the state’s resident population counts). On the other hand, personnel who are *stationed* or *assigned* overseas will be counted to their “home state of record” for apportionment purposes only and will show up as part of a state’s total “overseas count” when the Bureau releases the final and official apportionment data by December, 31, 2020. Military sources have told the Census Bureau that of all overseas military, approximately 15% are *deployed* personnel and 85% are *stationed* or *assigned* overseas.

Past apportionment studies by Election Data Services, Inc. can be found at <https://www.electiondataservices.com/reapportionment-studies/>. A historical chart on the number of districts each state received each decade from 1789 to current is also available at this web address and linkable at <https://www.electiondataservices.com/wp-content/uploads/2014/10/CD-apportionment-1789-2010.pdf>.

Election Data Services Inc. is a political consulting firm that specializes in redistricting, election administration, and the analysis of census and political data. Election Data Services, Inc. conducts the congressional apportionment analyses with each annual release of the census population estimates. For more information about the reapportionment analysis, contact Kimball Brace (703-580-7267 or 202-789-2004 or kbrace@electiondataservices.com).

¹ National Conference of State Legislatures reports 26 states have appropriated funds for Census counting. <http://www.ncsl.org/research/redistricting/2020-census-resources-and-legislation.aspx>

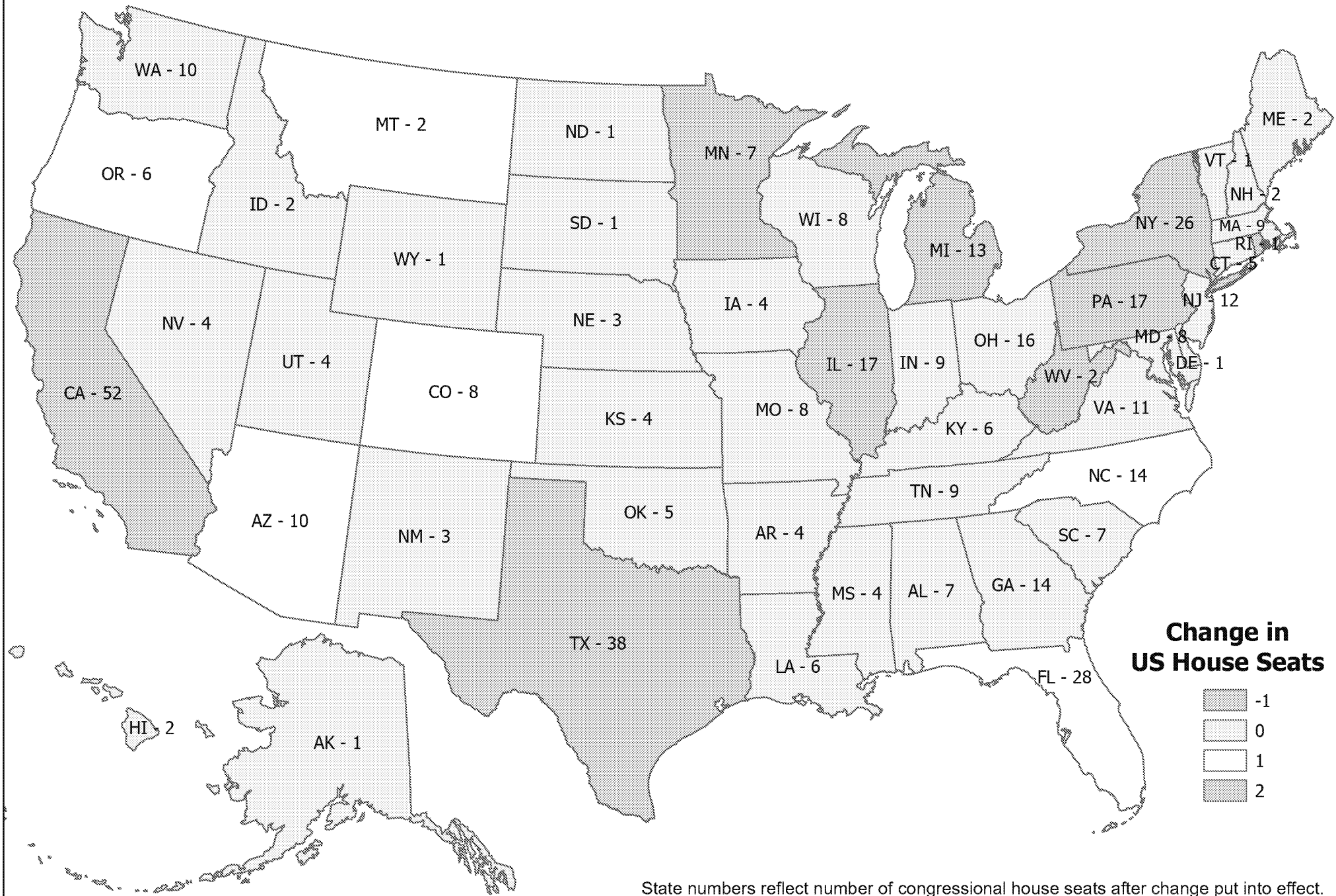
2019 Population Estimates 2019 Apportionment

| 2019 Population Estimates, Generated by Census Bureau 12/30/2019 | | | | | | | | | | |
|--|----------------------------|------------|-------|--------|-------------|-------------|-----------------|--------------|--------------|-----------|
| State | Population | Compare To | Seats | Change | Gain a Seat | Lose a Seat | Last Seat Given | Next Seat At | Average Size | Size Rank |
| Alabama | 4,903,185 | 7 | 7 | 0 | 743,187 | 18,516 | 433 | 502 | 700,455 | 43 |
| Alaska | 731,545 | 1 | 1 | 0 | | | at large | 637 | 731,545 | 34 |
| Arizona | 7,278,717 | 9 | 10 | 1 | 634,842 | 128,294 | 431 | 472 | 727,872 | 37 |
| Arkansas | 3,017,804 | 4 | 4 | 0 | 356,549 | 406,839 | 378 | 490 | 754,451 | 24 |
| California | 39,512,223 | 53 | 52 | -1 | 98,709 | 697,431 | 430 | 439 | 759,850 | 20 |
| Colorado | 5,758,736 | 7 | 8 | 1 | 643,648 | 118,406 | 428 | 487 | 719,842 | 39 |
| Connecticut | 3,565,287 | 5 | 5 | 0 | 567,434 | 194,546 | 413 | 507 | 713,057 | 40 |
| Delaware | 973,764 | 1 | 1 | 0 | | | at large | 477 | 973,764 | 2 |
| Florida | 21,477,737 | 27 | 28 | 1 | 23,006 | 753,842 | 421 | 436 | 767,062 | 15 |
| Georgia | 10,617,423 | 14 | 14 | 0 | 316,729 | 449,174 | 419 | 446 | 758,387 | 22 |
| Hawaii | 1,415,872 | 2 | 2 | 0 | 432,337 | 349,950 | 330 | 565 | 707,936 | 41 |
| Idaho | 1,787,065 | 2 | 2 | 0 | 61,144 | 721,143 | 262 | 449 | 893,533 | 4 |
| Illinois | 12,671,821 | 18 | 17 | -1 | 527,032 | 241,139 | 429 | 454 | 745,401 | 29 |
| Indiana | 6,732,219 | 9 | 9 | 0 | 425,864 | 336,686 | 417 | 465 | 748,024 | 28 |
| Iowa | 3,155,070 | 4 | 4 | 0 | 219,283 | 544,105 | 362 | 468 | 788,768 | 9 |
| Kansas | 2,913,314 | 4 | 4 | 0 | 461,039 | 302,349 | 393 | 505 | 728,329 | 36 |
| Kentucky | 4,467,673 | 6 | 6 | 0 | 422,229 | 339,375 | 402 | 474 | 744,612 | 30 |
| Louisiana | 4,648,794 | 6 | 6 | 0 | 241,108 | 520,496 | 390 | 459 | 774,799 | 11 |
| Maine | 1,344,212 | 2 | 2 | 0 | 503,997 | 278,290 | 344 | 597 | 672,106 | 46 |
| Maryland | 6,045,680 | 8 | 8 | 0 | 356,704 | 405,350 | 407 | 462 | 755,710 | 23 |
| Massachusetts | 6,892,503 | 9 | 9 | 0 | 265,580 | 496,970 | 405 | 451 | 765,834 | 16 |
| Michigan | 9,986,857 | 14 | 13 | -1 | 192,285 | 572,888 | 411 | 442 | 768,220 | 13 |
| Minnesota | 5,639,632 | 8 | 7 | -1 | 6,740 | 754,963 | 379 | 437 | 805,662 | 6 |
| Mississippi | 2,976,149 | 4 | 4 | 0 | 398,204 | 365,184 | 385 | 493 | 744,037 | 31 |
| Missouri | 6,137,428 | 8 | 8 | 0 | 264,956 | 497,098 | 399 | 456 | 767,179 | 14 |
| Montana | 1,068,778 | 1 | 2 | 1 | 779,431 | 2,856 | 434 | 734 | 534,389 | 50 |
| Nebraska | 1,934,408 | 3 | 3 | 0 | 679,355 | 88,177 | 418 | 586 | 644,803 | 47 |
| Nevada | 3,080,156 | 4 | 4 | 0 | 294,197 | 469,191 | 371 | 476 | 770,039 | 12 |
| New Hampshire | 1,359,711 | 2 | 2 | 0 | 488,498 | 293,789 | 339 | 589 | 679,856 | 45 |
| New Jersey | 8,882,190 | 12 | 12 | 0 | 541,864 | 222,598 | 426 | 464 | 740,183 | 32 |
| New Mexico | 2,096,829 | 3 | 3 | 0 | 516,934 | 250,598 | 387 | 542 | 698,943 | 44 |
| New York | 19,453,561 | 27 | 26 | -1 | 537,876 | 237,376 | 432 | 444 | 748,214 | 27 |
| North Carolina | 10,488,084 | 13 | 14 | 1 | 446,068 | 319,835 | 423 | 455 | 749,149 | 26 |
| North Dakota | 762,062 | 1 | 1 | 0 | | | at large | 613 | 762,062 | 18 |
| Ohio | 11,689,100 | 16 | 16 | 0 | 754,898 | 12,508 | 435 | 466 | 730,569 | 35 |
| Oklahoma | 3,956,971 | 5 | 5 | 0 | 175,750 | 586,230 | 374 | 457 | 791,394 | 8 |
| Oregon | 4,217,737 | 5 | 6 | 1 | 672,165 | 89,439 | 427 | 508 | 702,956 | 42 |
| Pennsylvania | 12,801,989 | 18 | 17 | -1 | 396,864 | 371,307 | 424 | 447 | 753,058 | 25 |
| Rhode Island | 1,059,361 | 2 | 1 | -1 | | | at large | 440 | 1,059,361 | 1 |
| South Carolina | 5,148,714 | 7 | 7 | 0 | 497,658 | 264,045 | 415 | 478 | 735,531 | 33 |
| South Dakota | 884,659 | 1 | 1 | 0 | | | at large | 524 | 884,659 | 5 |
| Tennessee | 6,829,174 | 9 | 9 | 0 | 328,909 | 433,641 | 409 | 458 | 758,797 | 21 |
| Texas | 28,995,881 | 36 | 38 | 2 | 51,004 | 733,864 | 425 | 438 | 763,050 | 17 |
| Utah | 3,205,958 | 4 | 4 | 0 | 168,395 | 594,993 | 355 | 460 | 801,490 | 7 |
| Vermont | 623,989 | 1 | 1 | 0 | | | at large | 729 | 623,989 | 48 |
| Virginia | 8,535,519 | 11 | 11 | 0 | 133,350 | 630,429 | 404 | 441 | 775,956 | 10 |
| Washington | 7,614,893 | 10 | 10 | 0 | 298,666 | 464,470 | 410 | 452 | 761,489 | 19 |
| West Virginia | 1,792,147 | 3 | 2 | -1 | 56,062 | 726,225 | 261 | 448 | 896,074 | 3 |
| Wisconsin | 5,822,434 | 8 | 8 | 0 | 579,950 | 182,104 | 422 | 480 | 727,804 | 38 |
| Wyoming | 578,759 | 1 | 1 | 0 | | | at large | 781 | 578,759 | 49 |
| Washington DC | 705,749 | 0 | | | | | | | | |
| | 328,239,523 | | 435 | | | | | Median = | 751,104 | |
| Other Inputs: | Seats to Apportion | | | | | | | Min = | 534,389 | |
| | 435 Max Seats to Calculate | | | | | | | Max = | 1,059,361 | |
| | 75 States | | | | | | | | | |
| | 50 | | | | | | | | | |
| <input type="checkbox"/> Include | | | | | | | | | | |

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Anticipated Gains/Losses in Reapportionment

2019 Population Estimates



State numbers reflect number of congressional house seats after change put into effect.

BC-DOC-CEN-2020-001602-001076

2020 Population Projections and Apportionment

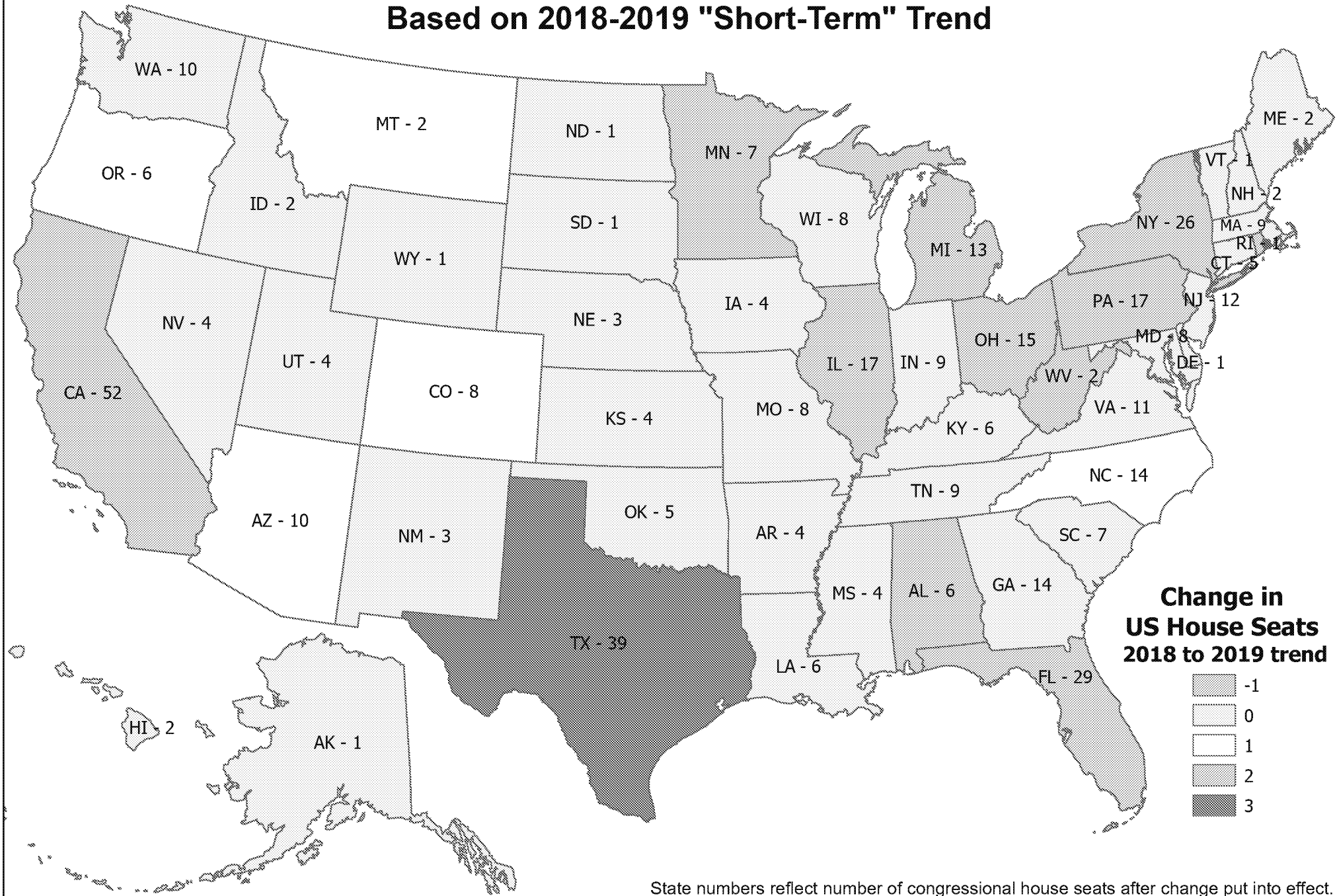
| 2020 Projections (short term 2018-2019 change) based on 2019 Population Estimates, Generated by Census Bureau 12/30/2019 | | | | | | | | | | |
|--|----------------------------|------------|-------|--------|-------------|-------------|-----------------|--------------|--------------|-----------|
| State | Population | Compare To | Seats | Change | Gain a Seat | Lose a Seat | Last Seat Given | Next Seat At | Average Size | Size Rank |
| Alabama | 4,914,850 | 7 | 6 | -1 | 10,072 | 761,044 | 371 | 436 | 819,142 | 6 |
| Alaska | 728,863 | 1 | 1 | 0 | | | at large | 640 | 728,863 | 38 |
| Arizona | 7,370,763 | 9 | 10 | 1 | 599,470 | 176,160 | 425 | 471 | 737,076 | 36 |
| Arkansas | 3,023,873 | 4 | 4 | 0 | 374,646 | 396,776 | 379 | 489 | 755,968 | 24 |
| California | 39,550,248 | 53 | 52 | -1 | 344,367 | 495,632 | 430 | 439 | 760,582 | 22 |
| Colorado | 5,809,922 | 7 | 8 | 1 | 638,314 | 134,743 | 426 | 485 | 726,240 | 40 |
| Connecticut | 3,560,620 | 5 | 5 | 0 | 601,698 | 169,052 | 416 | 508 | 712,124 | 41 |
| Delaware | 980,031 | 1 | 1 | 0 | | | at large | 475 | 980,031 | 2 |
| Florida | 21,654,726 | 27 | 29 | 2 | 760,045 | 44,285 | 435 | 447 | 746,715 | 29 |
| Georgia | 10,697,948 | 14 | 14 | 0 | 314,512 | 466,873 | 417 | 446 | 764,139 | 20 |
| Hawaii | 1,412,343 | 2 | 2 | 0 | 449,103 | 339,835 | 334 | 572 | 706,172 | 43 |
| Idaho | 1,815,033 | 2 | 2 | 0 | 46,412 | 742,526 | 261 | 443 | 907,517 | 3 |
| Illinois | 12,633,538 | 18 | 17 | -1 | 659,841 | 126,052 | 431 | 460 | 743,149 | 32 |
| Indiana | 6,759,912 | 9 | 9 | 0 | 449,436 | 324,863 | 415 | 464 | 751,101 | 27 |
| Iowa | 3,159,919 | 4 | 4 | 0 | 238,600 | 532,822 | 362 | 468 | 789,980 | 10 |
| Kansas | 2,914,781 | 4 | 4 | 0 | 483,738 | 287,684 | 395 | 507 | 728,695 | 39 |
| Kentucky | 4,472,570 | 6 | 6 | 0 | 452,352 | 318,764 | 402 | 478 | 745,428 | 31 |
| Louisiana | 4,640,641 | 6 | 6 | 0 | 284,281 | 486,835 | 392 | 461 | 773,440 | 14 |
| Maine | 1,348,093 | 2 | 2 | 0 | 513,353 | 275,585 | 342 | 596 | 674,047 | 46 |
| Maryland | 6,053,101 | 8 | 8 | 0 | 395,136 | 377,921 | 409 | 462 | 756,638 | 23 |
| Massachusetts | 6,899,915 | 9 | 9 | 0 | 309,433 | 464,866 | 406 | 453 | 766,657 | 18 |
| Michigan | 9,988,946 | 14 | 13 | -1 | 263,096 | 516,811 | 413 | 444 | 768,380 | 17 |
| Minnesota | 5,664,818 | 8 | 7 | -1 | 21,992 | 749,969 | 377 | 437 | 809,260 | 8 |
| Mississippi | 2,972,502 | 4 | 4 | 0 | 426,017 | 345,404 | 386 | 497 | 743,125 | 33 |
| Missouri | 6,149,312 | 8 | 8 | 0 | 298,924 | 474,133 | 400 | 457 | 768,664 | 15 |
| Montana | 1,074,909 | 1 | 2 | 1 | 786,537 | 2,402 | 434 | 735 | 537,455 | 50 |
| Nebraska | 1,941,034 | 3 | 3 | 0 | 691,448 | 83,395 | 418 | 587 | 647,011 | 47 |
| Nevada | 3,120,458 | 4 | 4 | 0 | 278,061 | 493,361 | 369 | 473 | 780,115 | 11 |
| New Hampshire | 1,364,417 | 2 | 2 | 0 | 497,029 | 291,909 | 339 | 589 | 682,209 | 45 |
| New Jersey | 8,879,315 | 12 | 12 | 0 | 612,232 | 166,218 | 429 | 465 | 739,943 | 35 |
| New Mexico | 2,099,901 | 3 | 3 | 0 | 532,581 | 242,263 | 387 | 542 | 699,967 | 44 |
| New York | 19,396,195 | 27 | 26 | -1 | 738,416 | 61,279 | 432 | 449 | 746,007 | 30 |
| North Carolina | 10,568,755 | 13 | 14 | 1 | 443,705 | 337,679 | 421 | 451 | 754,911 | 25 |
| North Dakota | 765,064 | 1 | 1 | 0 | | | at large | 612 | 765,064 | 19 |
| Ohio | 11,698,680 | 16 | 15 | -1 | 74,135 | 708,742 | 410 | 438 | 779,912 | 12 |
| Oklahoma | 3,969,576 | 5 | 5 | 0 | 192,743 | 578,008 | 374 | 456 | 793,915 | 9 |
| Oregon | 4,244,856 | 5 | 6 | 1 | 680,066 | 91,050 | 428 | 505 | 707,476 | 42 |
| Pennsylvania | 12,802,789 | 18 | 17 | -1 | 490,590 | 295,303 | 427 | 450 | 753,105 | 26 |
| Rhode Island | 1,060,167 | 2 | 1 | -1 | | | at large | 440 | 1,060,167 | 1 |
| South Carolina | 5,197,747 | 7 | 7 | 0 | 489,063 | 282,898 | 412 | 474 | 742,535 | 34 |
| South Dakota | 889,160 | 1 | 1 | 0 | | | at large | 525 | 889,160 | 5 |
| Tennessee | 6,872,698 | 9 | 9 | 0 | 336,649 | 437,649 | 408 | 458 | 763,633 | 21 |
| Texas | 29,274,825 | 36 | 39 | 3 | 740,080 | 79,742 | 433 | 442 | 750,637 | 28 |
| Utah | 3,245,917 | 4 | 4 | 0 | 152,602 | 618,820 | 350 | 454 | 811,479 | 7 |
| Vermont | 623,712 | 1 | 1 | 0 | | | at large | 731 | 623,712 | 48 |
| Virginia | 8,561,297 | 11 | 11 | 0 | 169,656 | 607,364 | 403 | 441 | 778,300 | 13 |
| Washington | 7,683,987 | 10 | 10 | 0 | 286,246 | 489,384 | 407 | 448 | 768,399 | 16 |
| West Virginia | 1,783,100 | 3 | 2 | -1 | 78,346 | 710,593 | 264 | 452 | 891,550 | 4 |
| Wisconsin | 5,833,734 | 8 | 8 | 0 | 614,502 | 158,555 | 424 | 483 | 729,217 | 37 |
| Wyoming | 579,629 | 1 | 1 | 0 | | | at large | 782 | 579,629 | 49 |
| Washington DC | 708,919 | 0 | | | | | | | | |
| | | | | | | | | | | |
| 329,418,113 | | | 435 | | | | | Median = | 754,008 | |
| Other Inputs: | Seats to Apportion | | | | | | | Min = | 537,455 | |
| | 435 Max Seats to Calculate | | | | | | | Max = | 1,060,167 | |
| | 75 States | | | | | | | | | |
| | 50 | | | | | | | | | |
| | | | | | | | | | | |
| <input type="checkbox"/> Include | | | | | | | | | | |

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Anticipated Gains/Losses in Reapportionment

2020 Population Projections

Based on 2018-2019 "Short-Term" Trend



2020 Population Projections and Apportionment

| 2020 Projections (short term 2017-2019 change) based on 2019 Population Estimates, Generated by Census Bureau 12/30/2019 | | | | | | | | | | |
|--|----------------------------|------------|-------|--------|-------------|-------------|-----------------|--------------|--------------|-----------|
| State | Population | Compare To | Seats | Change | Gain a Seat | Lose a Seat | Last Seat Given | Next Seat At | Average Size | Size Rank |
| Alabama | 4,914,010 | 7 | 6 | -1 | 12,184 | 760,914 | 372 | 436 | 819,002 | 6 |
| Alaska | 728,521 | 1 | 1 | 0 | | | at large | 640 | 728,521 | 39 |
| Arizona | 7,369,666 | 9 | 10 | 1 | 602,627 | 176,291 | 426 | 471 | 736,967 | 36 |
| Arkansas | 3,024,010 | 4 | 4 | 0 | 375,387 | 397,361 | 379 | 490 | 756,002 | 24 |
| California | 39,570,095 | 53 | 52 | -1 | 334,826 | 522,150 | 430 | 439 | 760,963 | 22 |
| Colorado | 5,815,246 | 7 | 8 | 1 | 634,656 | 141,036 | 425 | 485 | 726,906 | 40 |
| Connecticut | 3,562,290 | 5 | 5 | 0 | 601,104 | 171,301 | 416 | 508 | 712,458 | 41 |
| Delaware | 980,229 | 1 | 1 | 0 | | | at large | 475 | 980,229 | 2 |
| Florida | 21,675,262 | 27 | 29 | 2 | 745,300 | 68,512 | 433 | 447 | 747,423 | 29 |
| Georgia | 10,696,628 | 14 | 14 | 0 | 318,677 | 467,300 | 417 | 446 | 764,045 | 20 |
| Hawaii | 1,412,696 | 2 | 2 | 0 | 449,231 | 340,371 | 334 | 572 | 706,348 | 43 |
| Idaho | 1,814,121 | 2 | 2 | 0 | 47,806 | 741,797 | 261 | 444 | 907,061 | 3 |
| Illinois | 12,632,029 | 18 | 17 | -1 | 664,784 | 126,679 | 431 | 460 | 743,061 | 32 |
| Indiana | 6,760,331 | 9 | 9 | 0 | 450,878 | 326,382 | 415 | 464 | 751,148 | 27 |
| Iowa | 3,160,162 | 4 | 4 | 0 | 239,235 | 533,513 | 362 | 468 | 790,040 | 10 |
| Kansas | 2,915,040 | 4 | 4 | 0 | 484,357 | 288,392 | 395 | 507 | 728,760 | 38 |
| Kentucky | 4,473,470 | 6 | 6 | 0 | 452,724 | 320,373 | 402 | 478 | 745,578 | 31 |
| Louisiana | 4,640,670 | 6 | 6 | 0 | 285,525 | 487,573 | 392 | 461 | 773,445 | 14 |
| Maine | 1,347,838 | 2 | 2 | 0 | 514,089 | 275,513 | 343 | 597 | 673,919 | 46 |
| Maryland | 6,053,889 | 8 | 8 | 0 | 396,013 | 379,679 | 409 | 462 | 756,736 | 23 |
| Massachusetts | 6,904,829 | 9 | 9 | 0 | 306,381 | 470,880 | 406 | 453 | 767,203 | 18 |
| Michigan | 9,992,018 | 14 | 13 | -1 | 262,673 | 521,500 | 413 | 443 | 768,617 | 17 |
| Minnesota | 5,667,521 | 8 | 7 | -1 | 20,758 | 753,511 | 377 | 437 | 809,646 | 8 |
| Mississippi | 2,971,533 | 4 | 4 | 0 | 427,864 | 344,884 | 386 | 497 | 742,883 | 33 |
| Missouri | 6,149,020 | 8 | 8 | 0 | 300,882 | 474,810 | 400 | 457 | 768,628 | 16 |
| Montana | 1,074,984 | 1 | 2 | 1 | 786,943 | 2,659 | 435 | 735 | 537,492 | 50 |
| Nebraska | 1,941,398 | 3 | 3 | 0 | 691,764 | 84,077 | 418 | 587 | 647,133 | 47 |
| Nevada | 3,123,035 | 4 | 4 | 0 | 276,362 | 496,386 | 368 | 473 | 780,759 | 11 |
| New Hampshire | 1,363,841 | 2 | 2 | 0 | 498,086 | 291,516 | 339 | 589 | 681,920 | 45 |
| New Jersey | 8,880,940 | 12 | 12 | 0 | 613,059 | 169,331 | 429 | 465 | 740,078 | 35 |
| New Mexico | 2,098,725 | 3 | 3 | 0 | 534,436 | 241,405 | 387 | 543 | 699,575 | 44 |
| New York | 19,402,911 | 27 | 26 | -1 | 736,901 | 71,298 | 432 | 449 | 746,266 | 30 |
| North Carolina | 10,572,293 | 13 | 14 | 1 | 443,011 | 342,965 | 421 | 451 | 755,164 | 25 |
| North Dakota | 764,757 | 1 | 1 | 0 | | | at large | 612 | 764,757 | 19 |
| Ohio | 11,700,172 | 16 | 15 | -1 | 75,684 | 712,111 | 410 | 438 | 780,011 | 12 |
| Oklahoma | 3,966,654 | 5 | 5 | 0 | 196,740 | 575,666 | 374 | 458 | 793,331 | 9 |
| Oregon | 4,246,026 | 5 | 6 | 1 | 680,168 | 92,930 | 428 | 505 | 707,671 | 42 |
| Pennsylvania | 12,807,376 | 18 | 17 | -1 | 489,438 | 302,025 | 427 | 450 | 753,375 | 26 |
| Rhode Island | 1,060,749 | 2 | 1 | -1 | | | at large | 440 | 1,060,749 | 1 |
| South Carolina | 5,197,719 | 7 | 7 | 0 | 490,560 | 283,709 | 411 | 474 | 742,531 | 34 |
| South Dakota | 889,140 | 1 | 1 | 0 | | | at large | 525 | 889,140 | 5 |
| Tennessee | 6,875,125 | 9 | 9 | 0 | 336,085 | 441,175 | 408 | 456 | 763,903 | 21 |
| Texas | 29,265,114 | 36 | 39 | 3 | 757,545 | 75,018 | 434 | 442 | 750,388 | 28 |
| Utah | 3,246,633 | 4 | 4 | 0 | 152,765 | 619,984 | 350 | 455 | 811,658 | 7 |
| Vermont | 623,856 | 1 | 1 | 0 | | | at large | 731 | 623,856 | 48 |
| Virginia | 8,562,723 | 11 | 11 | 0 | 170,486 | 610,148 | 403 | 441 | 778,429 | 13 |
| Washington | 7,688,570 | 10 | 10 | 0 | 283,722 | 495,196 | 407 | 448 | 768,857 | 15 |
| West Virginia | 1,782,953 | 3 | 2 | -1 | 78,974 | 710,629 | 264 | 452 | 891,477 | 4 |
| Wisconsin | 5,834,594 | 8 | 8 | 0 | 615,308 | 160,384 | 424 | 483 | 729,324 | 37 |
| Wyoming | 578,695 | 1 | 1 | 0 | | | at large | 783 | 578,695 | 49 |
| Washington DC | 709,879 | 0 | | | | | | | | |
| | | | | | | | | | | |
| 329,489,985 | | | 435 | | | | | Median = | 754,269 | |
| Other Inputs: | Seats to Apportion | | | | | | | Min = | 537,492 | |
| | 435 Max Seats to Calculate | | | | | | | Max = | 1,060,749 | |
| | 75 States | | | | | | | | | |
| | 50 | | | | | | | | | |
| <input type="checkbox"/> Include | | | | | | | | | | |

2020 Population Projections and Apportionment

| 2020 Projections (mid- term 2015-2019 change) based on 2019 Population Estimates, Generated by Census Bureau 12/30/2019 | | | | | | | | | | |
|---|----------------------------|------------|-------|--------|-------------|-------------|-----------------|--------------|--------------|-----------|
| State | Population | Compare To | Seats | Change | Gain a Seat | Lose a Seat | Last Seat Given | Next Seat At | Average Size | Size Rank |
| Alabama | 4,912,817 | 7 | 6 | -1 | 19,074 | 760,729 | 372 | 436 | 818,803 | 6 |
| Alaska | 730,438 | 1 | 1 | 0 | | | at large | 638 | 730,438 | 37 |
| Arizona | 7,368,448 | 9 | 10 | 1 | 613,064 | 176,821 | 427 | 471 | 736,845 | 36 |
| Arkansas | 3,025,358 | 4 | 4 | 0 | 377,971 | 399,347 | 379 | 490 | 756,339 | 24 |
| California | 39,625,332 | 53 | 52 | -1 | 325,736 | 586,871 | 430 | 439 | 762,026 | 22 |
| Colorado | 5,819,773 | 7 | 8 | 1 | 637,588 | 146,941 | 425 | 485 | 727,472 | 40 |
| Connecticut | 3,561,218 | 5 | 5 | 0 | 606,991 | 171,053 | 415 | 508 | 712,244 | 41 |
| Delaware | 980,071 | 1 | 1 | 0 | | | at large | 475 | 980,071 | 2 |
| Florida | 21,730,551 | 27 | 29 | 2 | 715,938 | 129,049 | 432 | 447 | 749,329 | 29 |
| Georgia | 10,703,281 | 14 | 14 | 0 | 324,762 | 476,437 | 417 | 446 | 764,520 | 19 |
| Hawaii | 1,414,718 | 2 | 2 | 0 | 449,362 | 342,654 | 334 | 570 | 707,359 | 43 |
| Idaho | 1,814,667 | 2 | 2 | 0 | 49,413 | 742,603 | 261 | 444 | 907,333 | 3 |
| Illinois | 12,637,252 | 18 | 17 | -1 | 674,939 | 134,938 | 431 | 460 | 743,368 | 33 |
| Indiana | 6,755,866 | 9 | 9 | 0 | 463,683 | 323,479 | 416 | 465 | 750,652 | 28 |
| Iowa | 3,161,536 | 4 | 4 | 0 | 241,793 | 535,525 | 362 | 468 | 790,384 | 10 |
| Kansas | 2,914,122 | 4 | 4 | 0 | 489,206 | 288,111 | 395 | 507 | 728,531 | 39 |
| Kentucky | 4,475,565 | 6 | 6 | 0 | 456,326 | 323,477 | 402 | 478 | 745,927 | 31 |
| Louisiana | 4,645,835 | 6 | 6 | 0 | 286,056 | 493,748 | 392 | 461 | 774,306 | 14 |
| Maine | 1,347,239 | 2 | 2 | 0 | 516,841 | 275,174 | 344 | 598 | 673,619 | 46 |
| Maryland | 6,057,065 | 8 | 8 | 0 | 400,296 | 384,233 | 409 | 463 | 757,133 | 23 |
| Massachusetts | 6,911,196 | 9 | 9 | 0 | 308,353 | 478,809 | 406 | 452 | 767,911 | 18 |
| Michigan | 9,997,254 | 14 | 13 | -1 | 269,296 | 529,036 | 414 | 443 | 769,020 | 16 |
| Minnesota | 5,670,032 | 8 | 7 | -1 | 24,826 | 757,215 | 377 | 437 | 810,005 | 8 |
| Mississippi | 2,973,848 | 4 | 4 | 0 | 429,480 | 347,838 | 386 | 497 | 743,462 | 32 |
| Missouri | 6,149,879 | 8 | 8 | 0 | 307,482 | 477,047 | 400 | 456 | 768,735 | 17 |
| Montana | 1,076,227 | 1 | 2 | 1 | 787,853 | 4,163 | 435 | 735 | 538,113 | 50 |
| Nebraska | 1,942,679 | 3 | 3 | 0 | 693,527 | 85,810 | 418 | 587 | 647,560 | 47 |
| Nevada | 3,123,107 | 4 | 4 | 0 | 280,221 | 497,097 | 369 | 473 | 780,777 | 11 |
| New Hampshire | 1,364,168 | 2 | 2 | 0 | 499,912 | 292,104 | 340 | 589 | 682,084 | 45 |
| New Jersey | 8,884,864 | 12 | 12 | 0 | 620,113 | 175,371 | 429 | 466 | 740,405 | 35 |
| New Mexico | 2,098,247 | 3 | 3 | 0 | 537,959 | 241,378 | 388 | 543 | 699,416 | 44 |
| New York | 19,416,240 | 27 | 26 | -1 | 746,863 | 89,321 | 433 | 449 | 746,778 | 30 |
| North Carolina | 10,577,560 | 13 | 14 | 1 | 450,483 | 350,716 | 422 | 451 | 755,540 | 25 |
| North Dakota | 763,577 | 1 | 1 | 0 | | | at large | 614 | 763,577 | 21 |
| Ohio | 11,702,603 | 16 | 15 | -1 | 86,871 | 717,210 | 410 | 438 | 780,174 | 12 |
| Oklahoma | 3,965,980 | 5 | 5 | 0 | 202,229 | 575,815 | 375 | 458 | 793,196 | 9 |
| Oregon | 4,257,506 | 5 | 6 | 1 | 674,385 | 105,418 | 426 | 502 | 709,584 | 42 |
| Pennsylvania | 12,805,211 | 18 | 17 | -1 | 506,979 | 302,898 | 428 | 450 | 753,248 | 26 |
| Rhode Island | 1,059,981 | 2 | 1 | -1 | | | at large | 440 | 1,059,981 | 1 |
| South Carolina | 5,199,387 | 7 | 7 | 0 | 495,471 | 286,570 | 412 | 474 | 742,770 | 34 |
| South Dakota | 890,616 | 1 | 1 | 0 | | | at large | 526 | 890,616 | 5 |
| Tennessee | 6,875,411 | 9 | 9 | 0 | 344,138 | 443,024 | 408 | 457 | 763,935 | 20 |
| Texas | 29,297,864 | 36 | 39 | 3 | 759,514 | 114,857 | 434 | 442 | 751,227 | 27 |
| Utah | 3,251,140 | 4 | 4 | 0 | 152,189 | 625,129 | 350 | 455 | 812,785 | 7 |
| Vermont | 623,759 | 1 | 1 | 0 | | | at large | 731 | 623,759 | 48 |
| Virginia | 8,568,766 | 11 | 11 | 0 | 174,542 | 618,123 | 404 | 441 | 778,979 | 13 |
| Washington | 7,704,829 | 10 | 10 | 0 | 276,683 | 513,202 | 407 | 448 | 770,483 | 15 |
| West Virginia | 1,783,044 | 3 | 2 | -1 | 81,036 | 710,980 | 266 | 453 | 891,522 | 4 |
| Wisconsin | 5,834,087 | 8 | 8 | 0 | 623,274 | 161,255 | 424 | 483 | 729,261 | 38 |
| Wyoming | 577,489 | 1 | 1 | 0 | | | at large | 785 | 577,489 | 49 |
| Washington DC | 711,695 | 0 | | | | | | | | |
| | 329,739,397 | | 435 | | | | | Median = | 754,394 | |
| Other Inputs: | Seats to Apportion | | | | | | | Min = | 538,113 | |
| | 435 Max Seats to Calculate | | | | | | | Max = | 1,059,981 | |
| | 75 States | | | | | | | | | |
| | 50 | | | | | | | | | |
| <input type="checkbox"/> Include | | | | | | | | | | |

2020 Population Projections and Apportionment

| 2020 Projections (long- term 2011-2019 change) based on 2019 Population Estimates, Generated by Census Bureau 12/30/2019 | | | | | | | | | | |
|--|----------------------------|------------|-------|--------|-------------|-------------|-----------------|--------------|--------------|-----------|
| State | Population | Compare To | Seats | Change | Gain a Seat | Lose a Seat | Last Seat Given | Next Seat At | Average Size | Size Rank |
| Alabama | 4,913,158 | 7 | 6 | -1 | 17,500 | 760,782 | 372 | 436 | 818,860 | 6 |
| Alaska | 732,439 | 1 | 1 | 0 | | | at large | 637 | 732,439 | 37 |
| Arizona | 7,363,698 | 9 | 10 | 1 | 615,818 | 171,572 | 428 | 472 | 736,370 | 36 |
| Arkansas | 3,025,225 | 4 | 4 | 0 | 377,252 | 399,033 | 379 | 490 | 756,306 | 24 |
| California | 39,696,643 | 53 | 52 | -1 | 244,435 | 655,474 | 430 | 438 | 763,397 | 22 |
| Colorado | 5,825,957 | 7 | 8 | 1 | 629,790 | 152,731 | 425 | 485 | 728,245 | 40 |
| Connecticut | 3,563,145 | 5 | 5 | 0 | 604,021 | 172,745 | 415 | 508 | 712,629 | 41 |
| Delaware | 980,443 | 1 | 1 | 0 | | | at large | 475 | 980,443 | 2 |
| Florida | 21,733,957 | 27 | 29 | 2 | 706,919 | 130,957 | 433 | 447 | 749,447 | 29 |
| Georgia | 10,700,181 | 14 | 14 | 0 | 325,104 | 472,628 | 419 | 445 | 764,299 | 20 |
| Hawaii | 1,419,389 | 2 | 2 | 0 | 444,225 | 347,250 | 333 | 568 | 709,694 | 42 |
| Idaho | 1,808,554 | 2 | 2 | 0 | 55,060 | 736,415 | 261 | 446 | 904,277 | 3 |
| Illinois | 12,653,759 | 18 | 17 | -1 | 655,102 | 150,579 | 431 | 460 | 744,339 | 32 |
| Indiana | 6,753,109 | 9 | 9 | 0 | 464,634 | 320,276 | 416 | 465 | 750,345 | 28 |
| Iowa | 3,163,630 | 4 | 4 | 0 | 238,848 | 537,437 | 362 | 468 | 790,907 | 10 |
| Kansas | 2,917,511 | 4 | 4 | 0 | 484,966 | 291,318 | 395 | 507 | 729,378 | 38 |
| Kentucky | 4,477,052 | 6 | 6 | 0 | 453,606 | 324,676 | 404 | 477 | 746,175 | 31 |
| Louisiana | 4,655,763 | 6 | 6 | 0 | 274,894 | 503,388 | 392 | 461 | 775,961 | 14 |
| Maine | 1,345,723 | 2 | 2 | 0 | 517,891 | 273,585 | 344 | 599 | 672,862 | 46 |
| Maryland | 6,065,700 | 8 | 8 | 0 | 390,046 | 392,475 | 408 | 463 | 758,212 | 23 |
| Massachusetts | 6,919,755 | 9 | 9 | 0 | 297,989 | 486,922 | 406 | 452 | 768,862 | 18 |
| Michigan | 9,996,752 | 14 | 13 | -1 | 267,230 | 527,878 | 414 | 444 | 768,981 | 17 |
| Minnesota | 5,668,657 | 8 | 7 | -1 | 24,776 | 755,500 | 378 | 437 | 809,808 | 8 |
| Mississippi | 2,975,907 | 4 | 4 | 0 | 426,570 | 349,714 | 386 | 497 | 743,977 | 33 |
| Missouri | 6,149,601 | 8 | 8 | 0 | 306,145 | 476,376 | 400 | 458 | 768,700 | 19 |
| Montana | 1,075,958 | 1 | 2 | 1 | 787,656 | 3,819 | 435 | 735 | 537,979 | 50 |
| Nebraska | 1,943,643 | 3 | 3 | 0 | 691,904 | 86,645 | 418 | 587 | 647,881 | 47 |
| Nevada | 3,119,268 | 4 | 4 | 0 | 283,209 | 493,075 | 369 | 473 | 779,817 | 13 |
| New Hampshire | 1,363,526 | 2 | 2 | 0 | 500,088 | 291,387 | 340 | 589 | 681,763 | 45 |
| New Jersey | 8,887,290 | 12 | 12 | 0 | 615,310 | 177,193 | 429 | 466 | 740,608 | 35 |
| New Mexico | 2,098,377 | 3 | 3 | 0 | 537,171 | 241,378 | 388 | 544 | 699,459 | 44 |
| New York | 19,449,289 | 27 | 26 | -1 | 708,771 | 121,030 | 432 | 448 | 748,050 | 30 |
| North Carolina | 10,572,638 | 13 | 14 | 1 | 452,647 | 345,085 | 422 | 451 | 755,188 | 25 |
| North Dakota | 770,073 | 1 | 1 | 0 | | | at large | 608 | 770,073 | 15 |
| Ohio | 11,702,810 | 16 | 15 | -1 | 83,715 | 716,656 | 410 | 439 | 780,187 | 11 |
| Oklahoma | 3,973,480 | 5 | 5 | 0 | 193,687 | 583,080 | 374 | 456 | 794,696 | 9 |
| Oregon | 4,253,040 | 5 | 6 | 1 | 677,618 | 100,664 | 427 | 504 | 708,840 | 43 |
| Pennsylvania | 12,807,279 | 18 | 17 | -1 | 501,583 | 304,098 | 426 | 450 | 753,369 | 26 |
| Rhode Island | 1,059,899 | 2 | 1 | -1 | | | at large | 440 | 1,059,899 | 1 |
| South Carolina | 5,197,967 | 7 | 7 | 0 | 495,466 | 284,810 | 412 | 474 | 742,567 | 34 |
| South Dakota | 890,810 | 1 | 1 | 0 | | | at large | 526 | 890,810 | 5 |
| Tennessee | 6,872,183 | 9 | 9 | 0 | 345,561 | 439,350 | 409 | 459 | 763,576 | 21 |
| Texas | 29,350,998 | 36 | 39 | 3 | 698,863 | 165,968 | 434 | 442 | 752,590 | 27 |
| Utah | 3,247,776 | 4 | 4 | 0 | 154,702 | 621,583 | 351 | 455 | 811,944 | 7 |
| Vermont | 623,704 | 1 | 1 | 0 | | | at large | 732 | 623,704 | 48 |
| Virginia | 8,578,424 | 11 | 11 | 0 | 162,697 | 627,230 | 403 | 441 | 779,857 | 12 |
| Washington | 7,697,326 | 10 | 10 | 0 | 282,190 | 505,200 | 407 | 449 | 769,733 | 16 |
| West Virginia | 1,786,340 | 3 | 2 | -1 | 77,273 | 714,202 | 265 | 453 | 893,170 | 4 |
| Wisconsin | 5,833,642 | 8 | 8 | 0 | 622,104 | 160,417 | 424 | 483 | 729,205 | 39 |
| Wyoming | 579,855 | 1 | 1 | 0 | | | at large | 782 | 579,855 | 49 |
| Washington DC | 714,924 | 0 | | | | | | | | |
| | | | | | | | | | | |
| 329,956,225 | | | 435 | | | | | Median = | 754,279 | |
| Other Inputs: | Seats to Apportion | | | | | | | Min = | 537,979 | |
| | 435 Max Seats to Calculate | | | | | | | Max = | 1,059,899 | |
| | 75 States | | | | | | | | | |
| | 50 | | | | | | | | | |
| | | | | | | | | | | |
| <input type="checkbox"/> Include | | | | | | | | | | |

| | | 2020 Apportionment Calculations based on different trend lines coming from the 2019 Census Bureau Estimates | | | | | | | | | | | | | | | | | |
|----------------|------------|---|--------|-----------------|--------|-----------------|--------|-----------------|--------|-----------------|--------|-----------------|--------|-----------------|--------|-----------------|--------|-----------------|--------|
| | | 2010-2019 Trend | | 2011-2019 Trend | | 2012-2019 Trend | | 2013-2019 Trend | | 2014-2019 Trend | | 2015-2019 Trend | | 2016-2019 Trend | | 2017-2019 Trend | | 2018-2019 Trend | |
| State | Compare To | Seats | Change | Seats | Change | Seats | Change | Seats | Change | Seats | Change | Seats | Change | Seats | Change | Seats | Change | Seats | Change |
| Alabama | 7 | 6 | -1 | 6 | -1 | 6 | -1 | 6 | -1 | 6 | -1 | 6 | -1 | 6 | -1 | 6 | -1 | 6 | -1 |
| Alaska | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Arizona | 9 | 10 | 1 | 10 | 1 | 10 | 1 | 10 | 1 | 10 | 1 | 10 | 1 | 10 | 1 | 10 | 1 | 10 | 1 |
| Arkansas | 4 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 |
| California | 53 | 52 | -1 | 52 | -1 | 52 | -1 | 52 | -1 | 52 | -1 | 52 | -1 | 52 | -1 | 52 | -1 | 52 | -1 |
| Colorado | 7 | 8 | 1 | 8 | 1 | 8 | 1 | 8 | 1 | 8 | 1 | 8 | 1 | 8 | 1 | 8 | 1 | 8 | 1 |
| Connecticut | 5 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 |
| Delaware | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Florida | 27 | 29 | 2 | 29 | 2 | 29 | 2 | 29 | 2 | 29 | 2 | 29 | 2 | 29 | 2 | 29 | 2 | 29 | 2 |
| Georgia | 14 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 |
| Hawaii | 2 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 |
| Idaho | 2 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 |
| Illinois | 18 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 |
| Indiana | 9 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 |
| Iowa | 4 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 |
| Kansas | 4 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 |
| Kentucky | 6 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 |
| Louisiana | 6 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 | 6 | 0 |
| Maine | 2 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 |
| Maryland | 8 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 |
| Massachusetts | 9 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 |
| Michigan | 14 | 13 | -1 | 13 | -1 | 13 | -1 | 13 | -1 | 13 | -1 | 13 | -1 | 13 | -1 | 13 | -1 | 13 | -1 |
| Minnesota | 8 | 7 | -1 | 7 | -1 | 7 | -1 | 7 | -1 | 7 | -1 | 7 | -1 | 7 | -1 | 7 | -1 | 7 | -1 |
| Mississippi | 4 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 |
| Missouri | 8 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 |
| Montana | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 |
| Nebraska | 3 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 |
| Nevada | 4 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 |
| New Hampshire | 2 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 2 | 0 |
| New Jersey | 12 | 12 | 0 | 12 | 0 | 12 | 0 | 12 | 0 | 12 | 0 | 12 | 0 | 12 | 0 | 12 | 0 | 12 | 0 |
| New Mexico | 3 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 |
| New York | 27 | 26 | -1 | 26 | -1 | 26 | -1 | 26 | -1 | 26 | -1 | 26 | -1 | 26 | -1 | 26 | -1 | 26 | -1 |
| North Carolina | 13 | 14 | 1 | 14 | 1 | 14 | 1 | 14 | 1 | 14 | 1 | 14 | 1 | 14 | 1 | 14 | 1 | 14 | 1 |
| North Dakota | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Ohio | 16 | 15 | -1 | 15 | -1 | 15 | -1 | 15 | -1 | 15 | -1 | 15 | -1 | 15 | -1 | 15 | -1 | 15 | -1 |
| Oklahoma | 5 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 | 5 | 0 |
| Oregon | 5 | 6 | 1 | 6 | 1 | 6 | 1 | 6 | 1 | 6 | 1 | 6 | 1 | 6 | 1 | 6 | 1 | 6 | 1 |
| Pennsylvania | 18 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 | 17 | -1 |
| Rhode Island | 2 | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 |
| South Carolina | 7 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 |
| South Dakota | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Tennessee | 9 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 |
| Texas | 36 | 39 | 3 | 39 | 3 | 39 | 3 | 39 | 3 | 39 | 3 | 39 | 3 | 39 | 3 | 39 | 3 | 39 | 3 |
| Utah | 4 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 |
| Vermont | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Virginia | 11 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 |
| Washington | 10 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 |
| West Virginia | 3 | 2 | -1 | 2 | -1 | 2 | -1 | 2 | -1 | 2 | -1 | 2 | -1 | 2 | -1 | 2 | -1 | 2 | -1 |
| Wisconsin | 8 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 | 8 | 0 |
| Wyoming | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Washington DC | 0 | | | | | | | | | | | | | | | | | | |
| | | 435 | | 435 | | 435 | | 435 | | 435 | | 435 | | 435 | | 435 | | 435 | |
| | | State | Seat | State | Seat | State | Seat | State | Seat | State | Seat | State | Seat | State | Seat | State | Seat | State | Seat |
| | 430 | California | 52 | California | 52 | California | 52 | California | 52 | California | 52 | California | 52 | California | 52 | California | 52 | California | 52 |
| | 431 | Illinois | 17 | Illinois | 17 | Illinois | 17 | Illinois | 17 | Illinois | 17 | Illinois | 17 | Illinois | 17 | Illinois | 17 | Illinois | 17 |
| | 432 | New York | 26 | New York | 26 | Florida | 29 | Florida | 29 | Florida | 29 | Florida | 29 | Florida | 29 | New York | 26 | New York | 26 |
| | 433 | Texas | 39 | Florida | 29 | New York | 26 | New York | 26 | New York | 26 | New York | 26 | New York | 26 | Florida | 29 | Texas | 39 |
| | 434 | Florida | 29 | Texas | 39 | Texas | 39 | Texas | 39 | Texas | 39 | Texas | 39 | Texas | 39 | Montana | 2 | Montana | 2 |
| | 435 | Montana | 2 | Montana | 2 | Montana | 2 | Montana | 2 | Montana | 2 | Montana | 2 | Montana | 2 | Texas | 39 | Montana | 2 |
| | 436 | Alabama | 7 | Alabama | 7 | Alabama | 7 | Alabama | 7 | Alabama | 7 | Alabama | 7 | Alabama | 7 | Alabama | 7 | Alabama | 7 |
| | 437 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 | Minnesota | 8 |
| | 438 | California | 53 | California | 53 | California | 53 | California | 53 | Ohio | 16 | Ohio | 16 | Ohio | 16 | Ohio | 16 | Ohio | 16 |
| | 439 | Ohio | 16 | Ohio | 16 | Ohio | 16 | Ohio | 16 | California | 53 | California | 53 | California | 53 | California | 53 | California | 53 |
| | 440 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 | Rhode Island | 2 |

| | 2016 Presidential Election | | | | | | | | |
|----------------|---|--------------------------------------|--|--|--|--|--|---|---|
| | New Apportionment Count (2018- 2019 Trend) | New Electoral College Count | 2010s Electoral College Count | 2000s Electoral College Count | 2016 Presidentia l Victor | Electoral Votes For Clinton (D) | Electoral Votes For Trump (Rep) | Revised Electoral Votes For Clinton (D) | Revised Electoral Votes For Trump (Rep) |
| State | | | | | | | | | |
| Alabama | 6 | 8 | 9 | 9 | Trump | 0 | 9 | 0 | 8 |
| Alaska | 1 | 3 | 3 | 3 | Trump | 0 | 3 | 0 | 3 |
| Arizona | 10 | 12 | 11 | 10 | Trump | 0 | 11 | 0 | 12 |
| Arkansas | 4 | 6 | 6 | 6 | Trump | 0 | 6 | 0 | 6 |
| California | 52 | 54 | 55 | 55 | Clinton | 55 | 0 | 54 | 0 |
| Colorado | 8 | 10 | 9 | 9 | Clinton | 9 | 0 | 10 | 0 |
| Connecticut | 5 | 7 | 7 | 7 | Clinton | 7 | 0 | 7 | 0 |
| Delaware | 1 | 3 | 3 | 3 | Clinton | 3 | 0 | 3 | 0 |
| Florida | 29 | 31 | 29 | 27 | Trump | 0 | 29 | 0 | 31 |
| Georgia | 14 | 16 | 16 | 15 | Trump | 0 | 16 | 0 | 16 |
| Hawaii | 2 | 4 | 4 | 4 | Clinton* | 3 | 0 | 3 | 0 |
| Idaho | 2 | 4 | 4 | 4 | Trump | 0 | 4 | 0 | 4 |
| Illinois | 17 | 19 | 20 | 21 | Clinton | 20 | 0 | 19 | 0 |
| Indiana | 9 | 11 | 11 | 11 | Trump | 0 | 11 | 0 | 11 |
| Iowa | 4 | 6 | 6 | 7 | Trump | 0 | 6 | 0 | 6 |
| Kansas | 4 | 6 | 6 | 6 | Trump | 0 | 6 | 0 | 6 |
| Kentucky | 6 | 8 | 8 | 8 | Trump | 0 | 8 | 0 | 8 |
| Louisiana | 6 | 8 | 8 | 9 | Trump | 0 | 8 | 0 | 8 |
| Maine | 2 | 4 | 4 | 4 | Clinton | 3 | 1 | 4 | 0 |
| Maryland | 8 | 10 | 10 | 10 | Clinton | 10 | 0 | 10 | 0 |
| Massachusetts | 9 | 11 | 11 | 12 | Clinton | 11 | 0 | 11 | 0 |
| Michigan | 13 | 15 | 16 | 17 | Trump | 0 | 16 | 0 | 15 |
| Minnesota | 7 | 9 | 10 | 10 | Clinton | 10 | 0 | 9 | 0 |
| Mississippi | 4 | 6 | 6 | 6 | Trump | 0 | 6 | 0 | 6 |
| Missouri | 8 | 10 | 10 | 11 | Trump | 0 | 10 | 0 | 10 |
| Montana | 2 | 4 | 3 | 3 | Trump | 0 | 3 | 0 | 4 |
| Nebraska | 3 | 5 | 5 | 5 | Trump | 0 | 5 | 0 | 5 |
| Nevada | 4 | 6 | 6 | 5 | Clinton | 6 | 0 | 6 | 0 |
| New Hampshire | 2 | 4 | 4 | 4 | Clinton | 4 | 0 | 4 | 0 |
| New Jersey | 12 | 14 | 14 | 15 | Clinton | 14 | 0 | 14 | 0 |
| New Mexico | 3 | 5 | 5 | 5 | Clinton | 5 | 0 | 5 | 0 |
| New York | 26 | 28 | 29 | 31 | Clinton | 29 | 0 | 28 | 0 |
| North Carolina | 14 | 16 | 15 | 15 | Trump | 0 | 15 | 0 | 16 |
| North Dakota | 1 | 3 | 3 | 3 | Trump | 0 | 3 | 0 | 3 |
| Ohio | 15 | 17 | 18 | 20 | Trump | 0 | 18 | 0 | 17 |
| Oklahoma | 5 | 7 | 7 | 7 | Trump | 0 | 7 | 0 | 7 |
| Oregon | 6 | 8 | 7 | 7 | Clinton | 7 | 0 | 8 | 0 |
| Pennsylvania | 17 | 19 | 20 | 21 | Trump | 0 | 20 | 0 | 19 |
| Rhode Island | 1 | 3 | 4 | 4 | Clinton | 4 | 0 | 3 | 0 |
| South Carolina | 7 | 9 | 9 | 8 | Trump | 0 | 9 | 0 | 9 |
| South Dakota | 1 | 3 | 3 | 3 | Trump | 0 | 3 | 0 | 3 |
| Tennessee | 9 | 11 | 11 | 11 | Trump | 0 | 11 | 0 | 11 |
| Texas | 39 | 41 | 38 | 34 | Trump# | 0 | 36 | 0 | 39 |
| Utah | 4 | 6 | 6 | 5 | Trump | 0 | 6 | 0 | 6 |
| Vermont | 1 | 3 | 3 | 3 | Clinton | 3 | 0 | 3 | 0 |
| Virginia | 11 | 13 | 13 | 13 | Clinton | 13 | 0 | 13 | 0 |
| Washington | 10 | 12 | 12 | 11 | Clinton& | 8 | 0 | 8 | 0 |
| West Virginia | 2 | 4 | 5 | 5 | Trump | 0 | 5 | 0 | 4 |
| Wisconsin | 8 | 10 | 10 | 10 | Trump | 0 | 10 | 0 | 10 |
| Wyoming | 1 | 3 | 3 | 3 | Trump | 0 | 3 | 0 | 3 |
| Washington DC | 1 | 3 | 3 | 3 | Clinton | 3 | 0 | 3 | 0 |
| | | | | | | 227 | 304 | 225 | 306 |
| | | | | | | | | -2 | 2 |
| | | | | | #One elector voted for John Kasich for President | | | | |
| | | | | | #One elector voted for Ron Paul for President | | | | |
| | | | | | &Three electors voted for Colin Powell for President | | | | |
| | | | | | &One elector voted for Faith Spotted Eagle | | | | |
| | | | | | *One elector voted for Bernie Sanders | | | | |

| 2012 Presidential Election | | | | | 2008 Presidential Election | | | | |
|--------------------------------|--|---|---|--|--------------------------------|--|---|---|--|
| 2012 Presidential Victor | Electoral Votes For Obama (D) | Electoral Votes For Romney (Rep) | Revised Electoral Votes For Obama (D) | Revised Electoral Votes For Romney (Rep) | 2008 Presidential Victor | Electoral Votes For Obama (D) | Electoral Votes For McCain (Rep) | Revised Electoral Votes For Obama (D) | Revised Electoral Votes For McCain (Rep) |
| Romney | 0 | 9 | 0 | 8 | McCain | 0 | 9 | 0 | 8 |
| Romney | 0 | 3 | 0 | 3 | McCain | 0 | 3 | 0 | 3 |
| Romney | 0 | 11 | 0 | 12 | McCain | 0 | 10 | 0 | 12 |
| Romney | 0 | 6 | 0 | 6 | McCain | 0 | 6 | 0 | 6 |
| Obama | 55 | 0 | 54 | 0 | Obama | 55 | 0 | 54 | 0 |
| Obama | 9 | 0 | 10 | 0 | Obama | 9 | 0 | 10 | 0 |
| Obama | 7 | 0 | 7 | 0 | Obama | 7 | 0 | 7 | 0 |
| Obama | 3 | 0 | 3 | 0 | Obama | 3 | 0 | 3 | 0 |
| Obama | 29 | 0 | 31 | 0 | Obama | 27 | 0 | 31 | 0 |
| Romney | 0 | 16 | 0 | 16 | McCain | 0 | 15 | 0 | 16 |
| Obama | 4 | 0 | 4 | 0 | Obama | 4 | 0 | 4 | 0 |
| Romney | 0 | 4 | 0 | 4 | McCain | 0 | 4 | 0 | 4 |
| Obama | 20 | 0 | 19 | 0 | Obama | 21 | 0 | 19 | 0 |
| Romney | 0 | 11 | 0 | 11 | Obama | 11 | 0 | 11 | 0 |
| Obama | 6 | 0 | 6 | 0 | Obama | 7 | 0 | 6 | 0 |
| Romney | 0 | 6 | 0 | 6 | McCain | 0 | 6 | 0 | 6 |
| Romney | 0 | 8 | 0 | 8 | McCain | 0 | 8 | 0 | 8 |
| Romney | 0 | 8 | 0 | 8 | McCain | 0 | 9 | 0 | 8 |
| Obama | 4 | 0 | 4 | 0 | Obama | 4 | 0 | 4 | 0 |
| Obama | 10 | 0 | 10 | 0 | Obama | 10 | 0 | 10 | 0 |
| Obama | 11 | 0 | 11 | 0 | Obama | 12 | 0 | 11 | 0 |
| Obama | 16 | 0 | 15 | 0 | Obama | 17 | 0 | 15 | 0 |
| Obama | 10 | 0 | 9 | 0 | Obama | 10 | 0 | 9 | 0 |
| Romney | 0 | 6 | 0 | 6 | McCain | 0 | 6 | 0 | 6 |
| Romney | 0 | 10 | 0 | 10 | McCain | 0 | 11 | 0 | 10 |
| Romney | 0 | 3 | 0 | 4 | McCain | 0 | 3 | 0 | 4 |
| Romney | 0 | 5 | 0 | 5 | McCain | 1 | 4 | 1 | 4 |
| Obama | 6 | 0 | 6 | 0 | Obama | 5 | 0 | 6 | 0 |
| Obama | 4 | 0 | 4 | 0 | Obama | 4 | 0 | 4 | 0 |
| Obama | 14 | 0 | 14 | 0 | Obama | 15 | 0 | 14 | 0 |
| Obama | 5 | 0 | 5 | 0 | Obama | 5 | 0 | 5 | 0 |
| Obama | 29 | 0 | 28 | 0 | Obama | 31 | 0 | 28 | 0 |
| Romney | 0 | 15 | 0 | 16 | Obama | 15 | 0 | 16 | 0 |
| Romney | 0 | 3 | 0 | 3 | McCain | 0 | 3 | 0 | 3 |
| Obama | 18 | 0 | 17 | 0 | Obama | 20 | 0 | 17 | 0 |
| Romney | 0 | 7 | 0 | 7 | McCain | 0 | 7 | 0 | 7 |
| Obama | 7 | 0 | 8 | 0 | Obama | 7 | 0 | 8 | 0 |
| Obama | 20 | 0 | 19 | 0 | Obama | 21 | 0 | 19 | 0 |
| Obama | 4 | 0 | 3 | 0 | Obama | 4 | 0 | 3 | 0 |
| Romney | 0 | 9 | 0 | 9 | McCain | 0 | 8 | 0 | 9 |
| Romney | 0 | 3 | 0 | 3 | McCain | 0 | 3 | 0 | 3 |
| Romney | 0 | 11 | 0 | 11 | McCain | 0 | 11 | 0 | 11 |
| Romney | 0 | 38 | 0 | 41 | McCain | 0 | 34 | 0 | 41 |
| Romney | 0 | 6 | 0 | 6 | McCain | 0 | 5 | 0 | 6 |
| Obama | 3 | 0 | 3 | 0 | Obama | 3 | 0 | 3 | 0 |
| Obama | 13 | 0 | 13 | 0 | Obama | 13 | 0 | 13 | 0 |
| Obama | 12 | 0 | 12 | 0 | Obama | 11 | 0 | 12 | 0 |
| Romney | 0 | 5 | 0 | 4 | McCain | 0 | 5 | 0 | 4 |
| Obama | 10 | 0 | 10 | 0 | Obama | 10 | 0 | 10 | 0 |
| Romney | 0 | 3 | 0 | 3 | McCain | 0 | 3 | 0 | 3 |
| Obama | 3 | 0 | 3 | 0 | Obama | 3 | 0 | 3 | 0 |
| | 332 | 206 | 328 | 210 | | 365 | 173 | 356 | 182 |
| | | | -4 | 4 | | | | -9 | 9 |
| | | | | | | | | | |
| | | | | | | | | | |
| | | | | | | | | | |
| | | | | | | | | | |

| 2004 Presidential Election | | | | | 2000 Presidential Election | | | | |
|--------------------------------|-------------------------------------|---|--|--|--------------------------------|------------------------------------|---|---|--|
| 2004 Presidential Victor | Electoral Votes For Kerry (D) | Electoral Votes For Bush (Rep) | Revised Electoral Votes For Kerry (D) | Revised Electoral Votes For Bush (Rep) | 2000 Presidential Victor | Electoral Votes For Gore (D) | Electoral Votes For Bush (Rep) | Revised Electoral Votes For Gore (D) | Revised Electoral Votes For Bush (Rep) |
| Bush | 0 | 9 | 0 | 8 | Bush | 0 | 9 | 0 | 8 |
| Bush | 0 | 3 | 0 | 3 | Bush | 0 | 3 | 0 | 3 |
| Bush | 0 | 10 | 0 | 12 | Bush | 0 | 8 | 0 | 12 |
| Bush | 0 | 6 | 0 | 6 | Bush | 0 | 6 | 0 | 6 |
| Kerry | 55 | 0 | 54 | 0 | Gore | 54 | 0 | 54 | 0 |
| Bush | 0 | 9 | 0 | 10 | Bush | 0 | 8 | 0 | 10 |
| Kerry | 7 | 0 | 7 | 0 | Gore | 8 | 0 | 7 | 0 |
| Kerry | 3 | 0 | 3 | 0 | Gore | 3 | 0 | 3 | 0 |
| Bush | 0 | 27 | 0 | 31 | Bush | 0 | 25 | 0 | 31 |
| Bush | 0 | 15 | 0 | 16 | Bush | 0 | 13 | 0 | 16 |
| Kerry | 4 | 0 | 4 | 0 | Gore | 4 | 0 | 4 | 0 |
| Bush | 0 | 4 | 0 | 4 | Bush | 0 | 4 | 0 | 4 |
| Kerry | 21 | 0 | 19 | 0 | Gore | 22 | 0 | 19 | 0 |
| Bush | 0 | 11 | 0 | 11 | Bush | 0 | 12 | 0 | 11 |
| Bush | 0 | 7 | 0 | 6 | Gore | 7 | 0 | 6 | 0 |
| Bush | 0 | 6 | 0 | 6 | Bush | 0 | 6 | 0 | 6 |
| Bush | 0 | 8 | 0 | 8 | Bush | 0 | 8 | 0 | 8 |
| Bush | 0 | 9 | 0 | 8 | Bush | 0 | 9 | 0 | 8 |
| Kerry | 4 | 0 | 4 | 0 | Gore | 4 | 0 | 4 | 0 |
| Kerry | 10 | 0 | 10 | 0 | Gore | 10 | 0 | 10 | 0 |
| Kerry | 12 | 0 | 11 | 0 | Gore | 12 | 0 | 11 | 0 |
| Kerry | 17 | 0 | 15 | 0 | Gore | 18 | 0 | 15 | 0 |
| Kerry | 9 | 0 | 8 | 0 | Gore | 10 | 0 | 9 | 0 |
| Bush | 0 | 6 | 0 | 6 | Bush | 0 | 7 | 0 | 6 |
| Bush | 0 | 11 | 0 | 10 | Bush | 0 | 11 | 0 | 10 |
| Bush | 0 | 3 | 0 | 4 | Bush | 0 | 3 | 0 | 4 |
| Bush | 0 | 5 | 0 | 5 | Bush | 0 | 5 | 0 | 5 |
| Bush | 0 | 5 | 0 | 6 | Bush | 0 | 4 | 0 | 6 |
| Kerry | 4 | 0 | 4 | 0 | Bush | 0 | 4 | 0 | 4 |
| Kerry | 15 | 0 | 14 | 0 | Gore | 15 | 0 | 14 | 0 |
| Bush | 0 | 5 | 0 | 5 | Gore | 5 | 0 | 5 | 0 |
| Kerry | 31 | 0 | 28 | 0 | Gore | 33 | 0 | 28 | 0 |
| Bush | 0 | 15 | 0 | 16 | Bush | 0 | 14 | 0 | 16 |
| Bush | 0 | 3 | 0 | 3 | Bush | 0 | 3 | 0 | 3 |
| Bush | 0 | 20 | 0 | 17 | Bush | 0 | 21 | 0 | 17 |
| Bush | 0 | 7 | 0 | 7 | Bush | 0 | 8 | 0 | 7 |
| Kerry | 7 | 0 | 8 | 0 | Gore | 7 | 0 | 8 | 0 |
| Kerry | 21 | 0 | 19 | 0 | Gore | 23 | 0 | 19 | 0 |
| Kerry | 4 | 0 | 3 | 0 | Gore | 4 | 0 | 3 | 0 |
| Bush | 0 | 8 | 0 | 9 | Bush | 0 | 8 | 0 | 9 |
| Bush | 0 | 3 | 0 | 3 | Bush | 0 | 3 | 0 | 3 |
| Bush | 0 | 11 | 0 | 11 | Bush | 0 | 11 | 0 | 11 |
| Bush | 0 | 34 | 0 | 41 | Bush | 0 | 32 | 0 | 41 |
| Bush | 0 | 5 | 0 | 6 | Bush | 0 | 5 | 0 | 6 |
| Kerry | 3 | 0 | 3 | 0 | Gore | 3 | 0 | 3 | 0 |
| Bush | 0 | 13 | 0 | 13 | Bush | 0 | 13 | 0 | 13 |
| Kerry | 11 | 0 | 12 | 0 | Gore | 11 | 0 | 12 | 0 |
| Bush | 0 | 5 | 0 | 4 | Bush | 0 | 5 | 0 | 4 |
| Kerry | 10 | 0 | 10 | 0 | Gore | 11 | 0 | 10 | 0 |
| Bush | 0 | 3 | 0 | 3 | Bush | 0 | 3 | 0 | 3 |
| Kerry | 3 | 0 | 3 | 0 | Gore | 2 | 0 | 2 | 0 |
| | 251 | 286 | 239 | 298 | | 266 | 271 | 246 | 291 |
| | | | -12 | 12 | | | | -20 | 20 |
| | | | | | | | | | |
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| | | | | | | | | | |

APPENDIX 3

(Exhibit 3 to Declaration of Kimball W. Brace)

| Report Date: 8/30/2020 As of 8/29/2020, percentage of housing units: | | | | |
|---|----------------|------------------------------|-------------|--|
| State | Self-Responded | Enumerated in Nonresponse | Enumerated | |
| U.S. Total | 64.9 | 16.9 | 81.7 | |
| Idaho | 68.6 | 27.8 | 96.5 | |
| West Virginia | 55.6 | 37.3 | 92.9 | |
| Washington | 71.1 | 20.5 | 91.5 | |
| Kansas | 68.6 | 22.4 | 91.0 | |
| Connecticut | 69.0 | 21.0 | 90.0 | |
| Oregon | 67.7 | 22.3 | 90.0 | |
| Maine | 57.0 | 32.9 | 89.8 | |
| Wisconsin | 71.1 | 18.7 | 89.8 | |
| Hawaii | 61.7 | 28.0 | 89.7 | |
| Indiana | 69.0 | 20.6 | 89.6 | |
| Minnesota | 73.8 | 14.0 | 87.9 | |
| Illinois | 69.6 | 18.1 | 87.7 | |
| Maryland | 69.2 | 17.3 | 86.5 | |
| Missouri | 64.6 | 22.0 | 86.5 | |
| California | 67.1 | 18.8 | 85.9 | |
| Massachusetts | 67.3 | 18.7 | 85.9 | |
| Alaska | 52.8 | 32.3 | 85.1 | |
| Utah | 69.3 | 15.8 | 85.1 | |
| Pennsylvania | 67.7 | 17.4 | 85.0 | |
| Ohio | 69.0 | 15.9 | 84.9 | |
| North Dakota | 63.9 | 20.2 | 84.1 | |
| Nebraska | 70.4 | 13.6 | 84.0 | |
| Virginia | 69.4 | 14.2 | 83.7 | |
| Colorado | 68.2 | 15.3 | 83.5 | |
| Arkansas | 59.3 | 23.7 | 83.0 | |
| Tennessee | 64.2 | 18.1 | 82.2 | |
| Michigan | 69.9 | 11.9 | 81.8 | |
| Rhode Island | 62.8 | 19.0 | 81.8 | |
| New Jersey | 66.9 | 14.1 | 81.0 | |
| Vermont | 58.7 | 22.1 | 80.8 | |
| New Hampshire | 64.9 | 15.8 | 80.7 | |
| Kentucky | 67.0 | 13.4 | 80.4 | |
| South Dakota | 65.5 | 14.5 | 80.0 | |
| District of Columbia | 61.3 | 18.5 | 79.7 | |
| New York | 61.0 | 17.9 | 78.8 | |
| Delaware | 62.4 | 16.1 | 78.5 | |
| Iowa | 69.7 | 08.8 | 78.5 | |
| Nevada | 64.1 | 14.3 | 78.5 | |
| Oklahoma | 59.2 | 19.3 | 78.5 | |
| Wyoming | 59.2 | 19.1 | 78.3 | |
| Texas | 60.2 | 17.5 | 77.7 | |
| Florida | 61.5 | 13.3 | 74.8 | |
| Louisiana | 58.3 | 16.2 | 74.4 | |
| North Carolina | 60.7 | 13.6 | 74.3 | |
| Mississippi | 58.9 | 14.8 | 73.7 | |
| South Carolina | 58.7 | 14.7 | 73.4 | |
| Montana | 58.1 | 15.2 | 73.3 | |
| Alabama | 61.8 | 11.2 | 73.0 | |
| Arizona | 61.3 | 11.5 | 72.9 | |
| Puerto Rico | 32.2 | 40.6 | 72.8 | |
| Georgia | 60.2 | 12.5 | 72.7 | |
| New Mexico | 55.6 | 15.6 | 71.2 | |

EXHIBIT D

**UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF MARYLAND**

LA UNIÓN DEL PUEBLO ENTERO, et al.,

Plaintiffs,

v.

DONALD J. TRUMP, sued in his official
capacity as President of the United States, et
al.,

Defendants.

Civil Action No. 8:19-CV-02710-PX

DECLARATION OF AMY O'HARA

I. QUALIFICATIONS

1. I am a Research Professor in the Massive Data Institute at the McCourt School of Public Policy at Georgetown University and Executive Director of Georgetown's Federal Statistical Research Data Center. I have been in this role at Georgetown since 2018, where I focus on the secure and responsible use of administrative data for research and statistical purposes. I lead a team that develops governance models, data access protocols, and research methods to advance ethical and privacy preserving data uses. I have a Ph.D. in economics from the University of Notre Dame. A copy of my CV is attached to this declaration.

2. Prior to entering academia, I worked at the U.S. Census Bureau for fourteen years. I am the former chief of the Center for Administrative Records Research and Applications (CARRA), where I designed and led the data acquisition, linkage, and research activities using federal, state, and local administrative data. As the senior executive over administrative data, I negotiated access and uses of data from dozens of agencies, and oversaw the data processing to enable matching across files. I designed and led the work on administrative records during the 2020 Research and Testing Program through 2012, and led negotiations to obtain administrative data for decennial census planning and operations through 2017. I have received the Department

of Commerce Gold Award for negotiating access to tax data for the 2020 census, and Census Bureau Bronze Award for work with administrative data. I was also awarded the 2012 Arthur S. Flemming Award for my leadership in expanding the use of administrative data in federal statistics.

3. I was retained by the plaintiffs in *La Unión del Pueblo Entero, et al., v. Trump, et al.*, No. 8:19-CV-02710 (D. Md.), to provide my expert opinion on the policies and procedures involving administrative records at the U.S. Census Bureau, and on the extent to which the Commerce Department and Census Bureau policies and protocols affect the accuracy of the 2020 Census.

4. I am being compensated at a rate of \$150 per hour.

II. SUMMARY AND CONCLUSIONS

5. Based on my experience and knowledge, the decision by the Census Bureau to end field operations and compress post data collection activities (referred to herein as “post-processing”) to deliver apportionment data by December 31, 2020 will require excessive reliance on administrative data and imputation methods that are very likely to produce undercounts through failure to enumerate individuals.

6. Based on my experience and knowledge of administrative data sources and quality, it is my opinion that truncating field operations and post-processing will strain currently developed methods and processes that are used to fill-in missing data and will reduce the accuracy of census counts and characteristics in the following ways:

- a. Shorter fieldwork may reduce the number of in-person or proxy responses obtained; this will then require more imputation.

- b. The administrative data sources currently planned for count imputation use have insufficient coverage for low-income and highly mobile households.
- c. Reduced fieldwork cannot be remedied by using administrative data.

III. PLANNED USES OF ADMINISTRATIVE RECORDS

7. The Census Bureau acquired administrative records from 2010 onwards, for research and testing, in order to determine how to assess quality and a source's fitness for use (e.g., different data are valuable for different uses, like filling in missing age or sex, or to help determine whether a unit is vacant). Data sources were identified, then data sharing agreements were negotiated between the Census Bureau and the relevant agency. Files were delivered, reviewed, and assessed to see how complete and accurate their data were. A set of data from federal, state, and commercial sources were built into an operational database for the 2020 census. These records were harmonized, or uniformly processed and ready to plug into census operations. The system was developed and tested over the past several years, and at the start of 2020 the system was expected to receive updates from its component sources during the year. The scale of data preparation was unprecedented for census operations, requiring billions of records to be normalized and readied for multiple uses. A typical census schedule required the parallel development of the MAF and field operations, but 2020 innovations also required coordination of the administrative data system and online response system. This was a huge and complex undertaking that received less testing than originally planned and had system integration challenges.

8. The pandemic rattled this undertaking. COVID-19 altered the economy, society, and census. Shifts in residential patterns, school closings, community lockdowns, and disruption of government programs and services were just a few of the factors that affected data streams

and census plans. Some families moved away from viral hotspots, families decided how to cohabitate to care for children and elders, higher education institutions sent students home, and many aspects of life shifted online as non-essential businesses were ordered closed in many places. Many government agencies and departments limited services, allowing extensions on everything from income tax filings to driver's license renewals. The economic shutdown caused a crush of filers and applicants for unemployment benefits and food assistance programs. All of this affected the both the data landscape and the enumeration itself. The Census Bureau faced uncertainty and delay over how the census fieldwork could occur, and has not released updated plans on how administrative data will be used. Based on my experience and knowledge, the policy setting and decision-making processes at the Census Bureau are unable to adapt quickly to address the effects of the pandemic.

9. According to Census Bureau plans, they hoped to have a self-response of 60% by mid-May, then send more than 420,000 field staff to conduct NRFU over a 15-week period from mid-May to mid-August 2020. That would have allowed the Census Bureau approximately twenty weeks (mid-August to December) to process the data to prepare the apportionment counts by December 31, 2020.

10. The Census Bureau announced it will end fieldwork on September 30, 2020, yet the counts are still due December 31, 2020 and the Census Bureau has hired far fewer enumerators than planned.

IV. AFFECT OF THE PANDEMIC ON THE INTENDED USE OF ADMINISTRATIVE RECORDS

11. Administrative data cannot fix all the issues created by the pandemic and the truncated schedule. Adhering to the end of year deadline compresses not only the fieldwork, but

also reduces the post-processing time. These two issues compound the risk of an inaccurate count. The goal of fieldwork is to obtain a count for each housing unit that has not yet responded. By limiting the number of weeks in the field, the Census Bureau risks its ability to visit housing units to assess whether they are vacant or occupied, and to arrange visits to obtain proxy responses from building managers in multi-unit buildings. If there are sections of cities or rural communities that fail to receive in-person visits, the Census Bureau will need to fill in missing data during post-processing in a time period of only about 13 weeks (October to December) to meet a December 31, 2020 apportionment count deadline. To recap, the Census Bureau was supposed to have 15 weeks in the field and will now have seven. They were supposed to have 20 weeks of post-processing and will now have 13.

12. After fieldwork is done, the Census Bureau needs to deal with missing data: If there is no self-response (from internet, phone, paper, or fieldwork) or proxy response for a housing unit, the Census Bureau will need to assess whether a non-responding unit was vacant or occupied. A number of administrative and commercial data sources are prepared for this assignment, but they have never been tested for the large volume of cases that will need to be processed. This brings a risk of using uneven USPS “vacant” designations from across the country and from differing types of addresses (e.g., non-city style addresses, apartment buildings with mail drops), and IRS data that may non-representative of the full population, undercounting minority groups.

13. Several of the administrative data sources tested for this use have had COVID challenges. The Census Bureau plan for count imputation is highly reliant on individual income tax data from the Internal Revenue Service (IRS). IRS data have substantial coverage of the U.S. population – hundreds of millions of records reflect person-address data on W-2s, information

returns about interest, mortgages, student loans, Social Security benefits, and contracting income. IRS income tax returns, filed on Form 1040s, often list an entire family or household and on-time returns are typically filed in early April, lining up well with Census Day of April 1. The pandemic affected timely filing, with business closures limiting the number of low-income filers who could visit retail tax preparers (or volunteer tax preparers at local libraries) in person. IRS offered a filing extension through July 15, 2020, though many individuals filed earlier to obtain their refunds or the economic stimulus payment that was administered through the tax system this spring. This stimulus payment may have increased the value of IRS records for the 2020 census, provided they arrive in time. The economic stimulus rebate administered during the last recession induced filing of millions of additional returns. However, IRS processing was disrupted due to the pandemic. A lack of transparency into the volume, coverage, and timeliness of administrative data like the IRS returns prompt questions over Census's possible expanded reliance on such sources.

14. The bulk of the tax records were expected in May and June. If the records come in late, post-processing will suffer delays and disruption. This calls into question whether the Census Bureau has adopted policies to address changes to administrative data delivery, content, or composition, and whether they can do all this work by December 31, 2020.

15. The Census Bureau invested in administrative data and methods expecting a much smaller workload to designate vacant, occupied, or delete status since they planned on being in the field for complete Non-Response Follow-Up operations. Given that the fieldwork will be cut short, the volume of addresses for which vacant/delete status must be identified will be greater.

V. ALTERNATIVE APPROACHES TO RESPOND TO THE PANDEMIC

16. The Census could use administrative data as planned to fill in missing data, but there are significant concerns about data availability. For example, as noted above, the Census Bureau's plans rely on heavy use of tax data, which does not include all households or children. With a larger than expected amount of missing data, this will result in biased responses and undercounts.

17. In order to maximize use of the administrative data, the Census Bureau would need to review the existing policies, assumptions, and rules of thumb embedded in their decisions. The Census Bureau has acquired, harmonized, and readied dozens of source files; many were evaluated during the decade and tested against 2010 or survey data, but were not deemed as highest quality by decennial planners. The 30+ administrative data sources ready for production¹ were assembled to support different operations. For example, some sources were tested and readied for vacant/delete checks, others were prepared for count imputation, and still other sources were best for characteristic imputation (e.g., where a household responds with a count but does not complete information on household member age or race). Operational tests had required the presence of two corroborating data points from the same or different data sources for inclusion in imputation processing.

18. Thus, it is possible that expanded administrative data use to fill in missing data could occur before traditional hot deck imputation. Hot deck imputation assigns a missing value (whether a household count, age, or sex) from another census record with similar characteristics. The "hot deck" is a set of records with similar variables such as age, race, and sex that provide

¹ "Intended Administrative Data Use in the 2020 Census," Karen D. Deaver, U.S. Census Bureau, May 1, 2020, <https://www2.census.gov/programs-surveys/decennial/2020/program-management/planning-docs/administrative-data-use-2020-census.pdf>.

the donor records for assignment. The Census Bureau has not released details on the characteristics of respondents or detailed geography of response patterns to demonstrate that available responses to act as donor households are sufficient for an increased use of imputation. In past censuses, the Census Bureau has imputed whole households, though at very low rates in any geography. Hot deck imputation at a greater level than previously applied could be risky during this census, especially with truncated fieldwork. This is because households who completed the census may not be representative of households who did not respond.

19. The 2020 census has been atypical in its conduct, timeline, response patterns, and underlying residential stability due to the pandemic. Based on my experience and knowledge, I do not believe that combining self-reported, proxy, and administrative data information was tested by the Census Bureau for imputation. The lack of uniform quality across sources, when census data were collected, the reference dates for administrative data, and lack of transparency about post-processing applied, leads to questionable overall data quality across the country and within population groups. Given these issues with administrative records, the lack of testing, and a drastically compressed schedule, based on my experience and knowledge, I do not believe maximizing administrative records use will be possible without serious risk to conducting an actual enumeration in the 2020 Census.

VI. CONCERNS WITH AVAILABLE ADMINISTRATIVE RECORDS

20. Census memos and publications have not described how the sources that have been prepared for operational use reflect the diverse population in the U.S. This calls into question the Census Bureau's ability to impute all ethnicity and race groups, and all age groups for every geography.

21. Earlier studies reveal that administrative data have lower coverage of groups including non-white and high mobility young adults.² An array of sources is needed to reflect the U.S. population, or you risk the results found in the 2010 Census Match Study³ that I designed and conducted with Sonya Porter and my staff in CARRA at the Census Bureau. That study, the first national assessment of how close an administrative data census could come to a traditional enumeration, revealed that administrative data were useful but the combination used in that study did not result in population totals that were consistent with a traditional census. The combination of commercial and federal administrative data sources provided low coverage of Hispanics, Native Hawaiian or Other Pacific Islander, and American Indian or Alaska Native race groups. These groups were also challenging to match across sources due to the Census Bureau's approach to person validation and linkage. A 2014 study noted that young children, minorities, residents of group quarters, immigrants, recent movers, low-income individuals, and non-employed individuals were less likely to receive a validated person linkage identifier.⁴ This is the same methodology being used for person validation and linkage for the 2020 census.

22. After the 2010 Census Match Study, the Census Bureau made efforts to improve administrative data coverage of the population, and to find sources of administrative data where earlier studies had revealed weaknesses. The composition of the records needs to be understood by age, sex, race, and Hispanic origin. Tax data misses many individuals who are not in the labor force, and will miss children in many households. This is why the now-dismantled Center for

² See Brittany Bond, J. David Brown, Adela Luque, Amy O'Hara, The Nature of the Bias When Studying Only Linkable Person Records: Evidence from the American Community Survey, U.S. Census Bureau (April 22, 2014), <https://www.census.gov/content/dam/Census/library/working-papers/2014/adrm/carra-wp-2014-08.pdf>.

³ "2010 Census Match Study," Sonya Rastogi and Amy O'Hara, U.S. Census Bureau, November 16, 2012, https://www.census.gov/2010census/pdf/2010_Census_Match_Study_Report.pdf.

⁴ Brittany Bond, J. David Brown, Adela Luque, Amy O'Hara, The Nature of the Bias When Studying Only Linkable Person Records: Evidence from the American Community Survey, U.S. Census Bureau (April 22, 2014), <https://www.census.gov/content/dam/Census/library/working-papers/2014/adrm/carra-wp-2014-08.pdf>.

Administrative Records Research and Applications pursued state health and human services program data. Dozens of datasets from state Supplemental Nutrition Assistance Programs, Women, Infant, and Children programs, and Temporary Assistance for Needy Families programs were accessed and harmonized. But according to its May 2020 memo, the Census Bureau does not plan to use any of these files for 2020 count imputation.

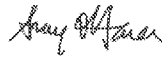
23. Increased reliance on administrative data in the post-processing period would require careful combination of sources and sufficient time to do it right. With the truncated schedule, there is not sufficient time. How administrative data would be summed when household members appear in multiple program files would need to be resolved. Adding sources together to get a total count may be appropriate in some households, but could erroneously reflect household size and composition in others. For example, a multigenerational household may have multiple tax returns, Medicare, and Housing and Urban Development mortgage administrative data, all reflecting a family under one roof. If the Census Bureau only counts one or two of these sources, family members would be missed and administrative data business rules would exacerbate an undercount. Research from Pew Research Center indicates that many multi-generational households are households with Hispanic, Black, and Asian heads, as well as immigrant households.⁵ Based on my knowledge and experience, it is unlikely that the Census Bureau has developed business rules or algorithms that properly blend sources together to accurately reflect household rosters. Such business rules and algorithms were not in place when I left in 2017 and have not been publicly shared since.

⁵ Paul Taylor, et al., *Fighting Poverty in a Tough Economy, Americans Move in with Their Relatives*, Pew Research Center, Chapter 3: Demographics of Multi-Generational Households (Oct. 3, 2011), <https://www.pewsocialtrends.org/2011/10/03/chapter-3-demographics-of-multi-generational-households/>.

VII. CONCLUSION

24. Because of insufficient quality administrative records available to address the various shortcomings resulting from a truncation of field operations and post-processing, based on my experience and knowledge, the Census Bureau must adhere to the requested plan extending statutory deadlines. Based on my knowledge and experience, the truncated schedule does not provide adequate time to meet these challenges, particularly given that career professionals at the Census Bureau said they needed until April 30, 2021, and the result of adhering to the truncated schedule will be a failure to conduct an actual enumeration of the population.

I declare under penalty of perjury that the foregoing is true and correct.



Amy O'Hara

Executed on August 31, 2020 at Silver Spring, Maryland.

APPENDIX 1

August 2019

AMY O'HARA
Curriculum Vitae

Massive Data Institute
Georgetown University
Washington DC 20057

650-680-5075
amy.ohara@georgetown.edu

EMPLOYMENT

Georgetown University

Research Professor, Massive Data Institute, 2018 - present
Director, Federal Statistical Research Data Center, 2018 - present

Stanford University

Senior Research Scholar, Stanford Institute for Economic Policy Research, 2017- 2018
Associate Director for Data, Stanford Center for Population Health Sciences, 2017-2018

U.S. Census Bureau

Chief, Center for Administrative Records Research and Applications, 2014-2017
Acting Chief, Center for Administrative Records Research and Applications, 2011-2014
Economist and Statistician, 2004-2011

EDUCATION

University of Notre Dame

Ph.D. in economics, 2003
M.A. in economics, 1998

State University of New York College at Buffalo

B.S. in economics, 1996

PUBLICATIONS

Medalia, Carla, Bruce Meyer, Amy O'Hara, and Derek Wu. 2019. "Linking Survey and Administrative Data to Measure Income, Inequality, and Mobility." *International Journal of Population Data Science*, 4(1):1-8.

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O'Hara, Amy. "Administrative Data Censuses in US States." In preparation.

O'Hara, Amy and Quentin Brummet. "The Differential Privacy Corner: What Has the US Backed Itself Into?" In preparation.

O'Hara, Amy. "Observing and Linking Household Relationships Across US Data Sources." In preparation. Uses decennial census, IRS 1040, Medicare, and Social Security Administration data.

REPORTS AND PERMANENT WORKING PAPERS

Postsecondary Data Infrastructure: What is Possible Today. Institute for Higher Education Policy. June 2019.

Developing, Validating, and Obtaining Stakeholder Buy-in for Criteria for Applying Social Science to Policymaking. With Fiona Fidler, Simine Vazire, Alexander Etz, Gary Klein, Richard Lempert, and Arthur Lupia. OSF Preprints. November 2018.

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Challenges to Evidence-Based Policy Making in the Decentralized U.S. Statistical System. With Nancy Potok and Ron Jarmin. 2014. Invited Paper for the Ninth International Conference on Teaching Statistics.

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The Effects of Taxes and Transfers on Income and Poverty in the United States: 2005. With Joseph Dalaker. 2007. P-60 Census Bureau Report.

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Tax Variable Imputation in the Current Population Survey. 2006. Proceedings of the 2006 IRS Research Conference.

Evaluation of CPS Tax Simulation Using Administrative IRS Data. 2005. Proceedings of the 2005 Federal Committee on Statistical Methodology Research Conference.

New Methods for Simulating CPS Taxes. 2004. Census Bureau Working Paper.

ORIGINAL DATA RESOURCES

Census Longitudinal Infrastructure Project (CLIP), Preliminary Release. U.S. Census Bureau. 2015. Co-founded CLIP to provide linked microdata from three decennial censuses, two household surveys (Current Population Survey and American Community Survey), and administrative records files from seven federal programs for researchers.

Parent-Child Pointer File (Census Kidlink), Preliminary Release. U.S. Census Bureau. 2013. The Census Kidlink file consists of parent-child linkages observed in Social Security card application data validated with IRS 1040 data. Census Bureau linkage keys are appended to mother-child and father-child relationships. The data are currently used in research projects, survey operations, and decennial census operations.

INVITED PRESENTATIONS

How Might Government Data be Leveraged for the Public Good? Brown Policy Lab, Rhode Island Office of Management and Budget. June 2019.

Supporting Data Access Within and Across Agencies. Committee for National Statistics. National Statistics for Public Policy Seminar. May 2019.

Implementation Issues for Secure Multiparty Computation. Will Secure Multiparty Computation Reshape Data Privacy? Open Technology Institute. April 2018.

Merging "Organic" and Administrative Data with Traditional Social Science Data. National Science Foundation Directorate for Social, Behavioral, and Economic Sciences Advisory Committee Meeting. October 2017.

The New Multiple Data Sources Paradigm for Federal Statistics: Progress and Prospects. Joint Statistical Meetings. August 2017.

The U.S. Census Bureau's Linkage Infrastructure: Overview and New Challenges. Data Linkage: Techniques, Challenges, and Applications, Newton Institute for Mathematical Sciences. September 2016.

The Opportunities and Challenges of Using and Linking Data. White House Office of Social Innovation Workshop. September 2016.

The Census Bureau Linkage Infrastructure. Joint Statistical Meetings. August 2016.

The Census Bureau Linkage Infrastructure. Pay for Success Convening, U.S. Department of Education. June 2016.

Use of Administrative Records to Reduce Burden and Improve Quality. Workshop on Respondent Burden in the American Community Survey. March 2016.

Census Bureau Efforts to Utilize and Share Data. The Promises and Challenges of Administrative Data in Social Policy Research, Department of Health and Human Services. October 2015.

Person Identification Validation System: the 2010 Census and the Coverage of Administrative Records. Inter-American Development Bank Conference on the Statistical Use of Administrative Registers. September 2015.

American Community Survey Administrative Records Research, Association of Public Data Users. September 2015.

Help Wanted. Keynote for Federal Computer Assisted Survey Information Collection Workshop. March 2015.

Data Integration to Evaluate Food Security Programs. Staff briefing for House Agriculture Committee. March 2015.

Data Access for Statistical Use of the National Directory of New Hires. Staff briefing for Senate Finance Committee. May 2015.

Information is Driving Innovation: How the Census Bureau is Integrating Administrative Records in the 2020 Census and Beyond. Staff briefing for House Appropriations Committee. March 2015.

Census Bureau Uses of New Data Sources. Privacy Working Group. February 2014.

Acquiring and Protecting Administrative Records: Current Programs and the Future. Future of Privacy Forum. September 2014.

GRANTS AND INSTITUTIONAL AWARDS

State Population Estimate Benchmarking (Co-Principal Investigator), funding by the Alfred P. Sloan Foundation, 2019-2021, \$600,000

Administrative Data Research Institute (Principal Investigator), funded by the Alfred P. Sloan Foundation, 2018-2020, \$1.7 million

2013 Gold Medal, U.S. Department of Commerce

2012 Arthur S. Flemming Award for Leadership and Management in Government Service

2010 Bronze Medal, U.S. Department of Commerce

PROFESSIONAL SERVICE

Invited Member, Health and Retirement Survey Data Monitoring Committee, 2019-2021

Invited Member, Evaluation Advisory Group, Future Skills Centre, 2019-2024

Canadian Future Skills Centre Evaluation Advisory Committee, 2019-present

Dutch Open Data Infrastructure for Social Science and Economic Innovations Advisory Board, 2020-2024

Invited Member, Panel on Improving Consumer Data for Food and Nutrition Policy Research for the Economic Research Service, 2018-present

Member, National Bureau of Economic Research Conference on Research in Income and Wealth

Invited Member, Panel on Modernizing the Nation's Crime Statistics, National Academies of Science, Engineering, and Medicine, 2013-2018

Criminal Justice Administrative Records System Board of Directors, University of Michigan, 2016-present

Manuscript reviewer for Journal of Human Resources, International Journal of Population and Data Science, Journal of Research on Educational Effectiveness, and Statistics and Public Policy

EXHIBIT C

**UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF MARYLAND**

LA UNIÓN DEL PUEBLO ENTERO, et al.,

Plaintiffs,

v.

DONALD J. TRUMP, sued in his official
capacity as President of the United States, et
al.,

Defendants.

Civil Action No. 8:19-CV-02710-PX

EXPERT DECLARATION OF DR. WILLIAM P. O'HARE

Overview

1. This report makes six key points:
 - a. Over the past several U.S. Censuses, the empirical evidence shows that groups with lower self-response rates have higher net undercounts and omission rates. This indicates that states and groups with lower self-response rates in the 2020 Census are likely to have higher net undercount and omission rates.
 - b. Census tracts where Hispanics and Blacks are the plurality of the population have lower self-response rates in the 2020 Census than tracts where Non-Hispanic Whites are the plurality of the population in the 2020 Census. This

indicates Hispanics and Blacks are likely to have higher net undercounts and omissions rates than Non-Hispanic Whites in the 2020 Census.

- c. Census tracts where the foreign-born population is a disproportionately high share of the tract population have lower self-response rates in the 2020 Census and are likely to have higher net undercounts and omissions rates than the native-born population in the 2020 census.
- d. Based on data from the 2010 and 2020 Census, households that respond later in the Census data collection period are disproportionately Hispanic, Asian, and Black rather than Non-Hispanic White. This means changes at or near the end of the data collection period are likely to have bigger impact on Hispanics, Asians, and Blacks.
- e. Net undercounts and omissions in the U.S. Census have important implications for the groups missed at the highest rates.
- f. Changing the end date of data collection in the 2020 Census from October 31, 2020 to September 30, 2020, will negatively impact the enumeration of Hispanic, Asians, and Blacks more than Non-Hispanic Whites.

Background

2. I have more than forty years of experience using Census data in a variety of professional settings, including experience in non-profits, philanthropy, state government, and university settings. Since 1987, I have worked at the Population Reference Bureau, the University of Louisville, and the Annie E. Casey Foundation.

3. I have a Bachelor of Science Degree from Michigan State University in Multi-Disciplinary Social Science. I have a master's degree from Michigan State University in Multi-disciplinary Social Science, I have a Ph.D. from Michigan State University in Sociology.

4. I have published many articles in scientific journals and written many books and book chapters based on Census Bureau data. I have authored more than a dozen monographs on subjects such as the well-being of children, poverty, and minorities in America. I have also made many presentations using Census data at professional conferences. While serving as the Director of the KIDS COUNT project within the Annie E. Casey Foundation from 1993 to 2006, I supervised the use of Census data related to measuring and reporting on the well-being of children.

5. I have been a member of the Population Association of America, the Southern Demographic Association, and the American Statistical Association since the 1970s.

6. I served on the Board of Directors and was President of the Southern Demographic Association. I was a founding member of the International Society of Child Indicators, and served on their Board of Directors for many years.

7. From 1995 to 2001, I was a representative from the American Statistical Association on the Census Bureau's Professional Advisory Committee. From 2008 to 2011, I was a representative from the Association of Public Data Users on the Census Bureau's 2010 Census Advisory Committee.

8. I was awarded a National Science Foundation/American Statistical Association/Census Bureau Research Fellowship to do research on census undercounts at the Census Bureau from 2011 to 2013.

9. In 1980, I was awarded a Fulbright Scholarship to teach demographic and social science research methods at the University of San Carlos in the Philippines during their 1980-81 school year.

10. I have been retained by Plaintiffs in *La Unión del Pueblo Entero v. Trump et al.*, Case No. 8-19-cv-02710 (D. Md.). I was asked to assess the impact of truncating the schedule for the 2020 Census, including moving the end date for 2020 Census data collection from October 31, 2020 to September 30, 2020.

11. I am being compensated at a rate of \$100 per hour.

I. The Link Between Self-Response Rates and Census Accuracy.

1.1 Key Concepts and Terms

12. Before presenting the analysis and results in this section of my report, it is important to define some key concepts and terms used in this report. The descriptions in this section of the report focus on census operations prior to the 2020 Census. Analysis in this section focuses on the relationship between census self-response and census accuracy. In the next sections, I focus on the 2020 Census.

1.1.2 Self-Response Rates

13. Briefly, the U.S. decennial Census can be thought of as having two major data collection phases: 1) a self-response phase and 2) a non-response followup (NRFU) phase. The self-response phase consists of households returning the questionnaire that was mailed to them from the Census Bureau. In the 2020 Census for the first time in the history of the decennial census, major modes of self-response operation will include internet and telephone responses

along with mail responses.¹ According to the U.S Census Bureau, (2020d) as of August 16, 2020, 80 percent of the responses submitted have been by Internet, 18.5 percent by paper, and 1.5 percent by telephone.

14. Several weeks after Census day (April 1) the second phase of the Census begins, and households that did not return a completed Census questionnaire are visited by a Census enumerator to gather the information needed for the Census. This is referred to as Nonresponse Followup ((NRFU) operation or phase by the Census Bureau.² A few people belatedly self-respond during the NRFU phase. There are also other Census operations (like update leave and update enumerate)³ that are outside of these two operations, but the vast majority of Census respondents are captured in the self-response and NRFU operations of the Census.

15. Self-response rates reflect the percent of households that return a completed Census questionnaire. In my analysis of the 1990, 2000 and 2010 Decennial Censuses, self-response is measured by two closely related indicators: mail return rates and mail response rates (because historically mail has been the primary mode of self-response). Detailed descriptions of mail return rates and the mail response rates are provided by the Census Bureau (2014b, page 61). In simple terms, the mail return rate is the percentage of occupied households that return completed Census questionnaires. Mail response rates are the percentages of Census questionnaires that were returned from all households whether they were occupied or not.

¹ In the 2010 Census, there were a very small number of people who were able to respond on the internet, but the internet option was not widely available

² The NRFU operational design in the 2020 Census will also use administrative records and third-party data to enumerate occupied housing units. See U.S. Census Bureau, *2020 Census Detailed Operational Plan: 18. Nonresponse Followup Operation (NRFU)*, April 2018 at 9, available at <https://www2.census.gov/programs-surveys/decennial/2020/program-management/planning-docs/NRFU-detailed-operational-plan.pdf>.

³ The Update/Leave operation is conducted in places without regular mail delivery. A census enumerator verifies a housing unit at the address and leaves a paper questionnaire for the household to complete. The Update/Enumerate operation is conducted in very remote areas.

Where available, my analysis uses mail return rate to measure self-response rates. However, the mail return rate was not available in the 1990 Census, so I use the mail response rate to reflect the self-response rate in 1990. As stated earlier, in the 2020 Census, other self-response modes, such as the internet and telephone, are available.

16. The mail return rates, and the mail response rates are calculated by the Census Bureau and these rates have been used by data analysts at the Census Bureau. The mail return rate was used by U.S. Census Bureau (2018d) to measure self-response in a study of the impact of a citizenship question on the 2020 Census questionnaire. In another Census Bureau analysis of the impact of a potential citizenship question on the 2020 Census, (2018b) Census Bureau staff also used self-response for both the 2010 and 2000 Census for which mail was the only self-response option, and for the American Community Survey (ACS) for which mail and internet self-responses were options.

1.3 Net Undercounts and Omissions

17. Net undercount and omissions rates are both measures of Census accuracy, but they capture different parts of Census accuracy (O'Hare 2019b).

18. The net undercount is a balance between people missed (omissions), those included erroneously (meaning those double counted and those inappropriately included in the census, like foreign tourists), and those imputed.⁴ If the number of omissions is higher than the number of erroneous inclusions and whole person imputations, there is a net undercount. If the number of erroneous inclusions and whole person imputations is larger than the number of omissions, there is a net overcount.

⁴ Imputations are people added to the Census count based on some evidence they exist. For example, if a housing unit looks occupied, but there is no self-response, and no one responds to an enumerator, the Census Bureau may impute people into the Census count.

19. In the 2010 Census there were 10,042,000 erroneous enumerations, 5,993,000 whole person imputations, and 15,999,000 omissions (U.S. Census Bureau 2012b, Table 3).

20. Omissions capture the number and share of a population that are missed in the Census and are defined by the Census Bureau (2012b, page 12), “omissions are people who should have been enumerated in the United States Census but were not.” In some ways omissions are a better reflection than net undercount rates of who is missed in the Census. For example, if 10 percent of Hispanics in a state are missed, while an equal number of Non-Hispanic Whites are double counted, the net undercount would be zero, but that does not reflect the fact that a large number of Hispanics were missed. The net undercount for a state can mask important differences in the accuracy of the census data across geographic subunits (like cities and counties) of the state.

21. It is important to understand the net undercount does not tell you how many people were missed in the Census and it is worth noting that even when a net undercount for a group is zero, there are often omissions. For example, the net undercount of Asians in the 2010 Census was essentially zero, but there was an omissions rate of over 5 percent for Asians in the 2010 Census. The net undercount for young children in the 2010 Census was 4.6 percent, but the omissions rate was 10.3 percent (O’Hare 2019a).

22. Undercounts have sometimes been reported as a negative number by the Census Bureau (Velkoff 2011; King et al. 2018; Jensen et al. 2018) and sometimes as a positive number by the U.S. Census Bureau (2012b). In this report, net undercounts are reported as a positive number and net overcounts as a negative number. Measuring net undercounts here as a positive number makes the correlations and the figures easier to interpret.

1.1.4 Correlations

23. Much of the analysis in this report relies on correlation coefficients to show relationships between two variables such as self-response rates and net undercount rates. More specifically, I use the Pearson Product-Moment Correlation Coefficient (Blalock 1972, page 376). This is probably the most widely used correlation calculation.

24. There are three dimensions of correlation coefficients: direction, magnitude, and statistical significance. Direction is indicated by a positive or a negative sign. A positive correlation indicates a higher value on one variable is associated with a higher value in the other variable. The relationship between height and weight reflects a positive correlation, i.e., taller people usually weigh more. A negative sign indicates that a higher value on one variable is associated with a lower value in the other variable. For example, the relationship between exercise and obesity reflects a negative correlation, i.e., people who exercise more are less likely to be obese.

25. The magnitude of a correlation coefficient varies from 0 to 1. A magnitude of zero means no relationship between the two variables and a value of 1 means a perfect correlation between the two variables. The higher the magnitude or value of the correlation coefficient the stronger the relationship between the two measures being examined. When you put direction and magnitude together the value can range from a -1 to +1, and the closer the correlation coefficient is to -1 or +1, the higher the correlation.

26. Statistical significance testing is done to assess how likely the observed results are due to chance. Researchers use different levels of statistical significance depending on the analysis. In this report, all the correlation coefficients deemed statistically significant are significant at the 0.10 level or higher (higher level of significance). This is a commonly used benchmark in social science research and the same level that the Census Bureau typically uses.

The standard used by the Census Bureau in its publications (U.S. Census Bureau 2017b, page 2) and on its website (U.S. Census Bureau 2018a, page 22) is 0.10, which means if something is statistically significant the results would occur by chance alone less than one time out of ten.⁵ Another way of saying this is that with a 0.10 level of significance we can be ninety percent confident the results reflect a real or true relationship between two measures. If the observed results are statistically significant, they are unlikely to be due to chance, and it is highly likely that a correlation coefficient that is statistically significant at the 0.10 level reflects a real relationship, and these are not random results. Most of the correlations in this report are statistically significant at a much higher level than 0.10

27. Since the key element of information needed for my analysis is to determine if a correlation coefficient is negative and statistically significant, a one-tailed test of significance is used. A one-tailed test implies we are only interested in seeing if the correlation is negative and statistically different from zero. This contrasts to a two-tailed test which would tell us if the correlation was statistically different from zero in either direction, that is positive or negative.

28. The statistical significance is largely determined by the size of the correlation and the number of observations upon which the correlation is based. Higher magnitude and more observations lead to a higher-level statistical significance.

1.2. Self-Response and Census Accuracy

29. In this section, I examine the relationship between self-response rates and Census accuracy, as measured by net undercount and omissions rates. The 1990, 2000, and 2010 Census

⁵ ACS “uses the Census Bureau’s standard 90% confidence level.” See American Community Survey Statistical Testing Tool, available at <https://www.census.gov/programs-surveys/acs/guidance/statistical-testing-tool.html>. “The Census Bureau uses 90 percent confidence intervals and 0.10 levels of significance to determine statistical validity.” Sources and Accuracy Estimates for Income and Poverty in the United States: 2016 and Health Insurance Coverage in the United States: 2016, available at <https://www2.census.gov/library/publications/2017/demo/p60-259sa.pdf>.

provide statistical data that can be used to examine this relationship from an empirical perspective. Relationships are shown graphically as well as statistically, as it may be easier to grasp a relationship from a visual presentation.

1.2.1 Examination of Data from the 2010 Census

30. Table 1.1 shows the self-response rates and net undercount rates for eight demographic groups defined by race, Hispanic origin, and tenure (i.e., owner or renter). These are the only demographic groups for which I could find all three measures (self-response, net undercount, and omissions rates) in consistently classified groups.

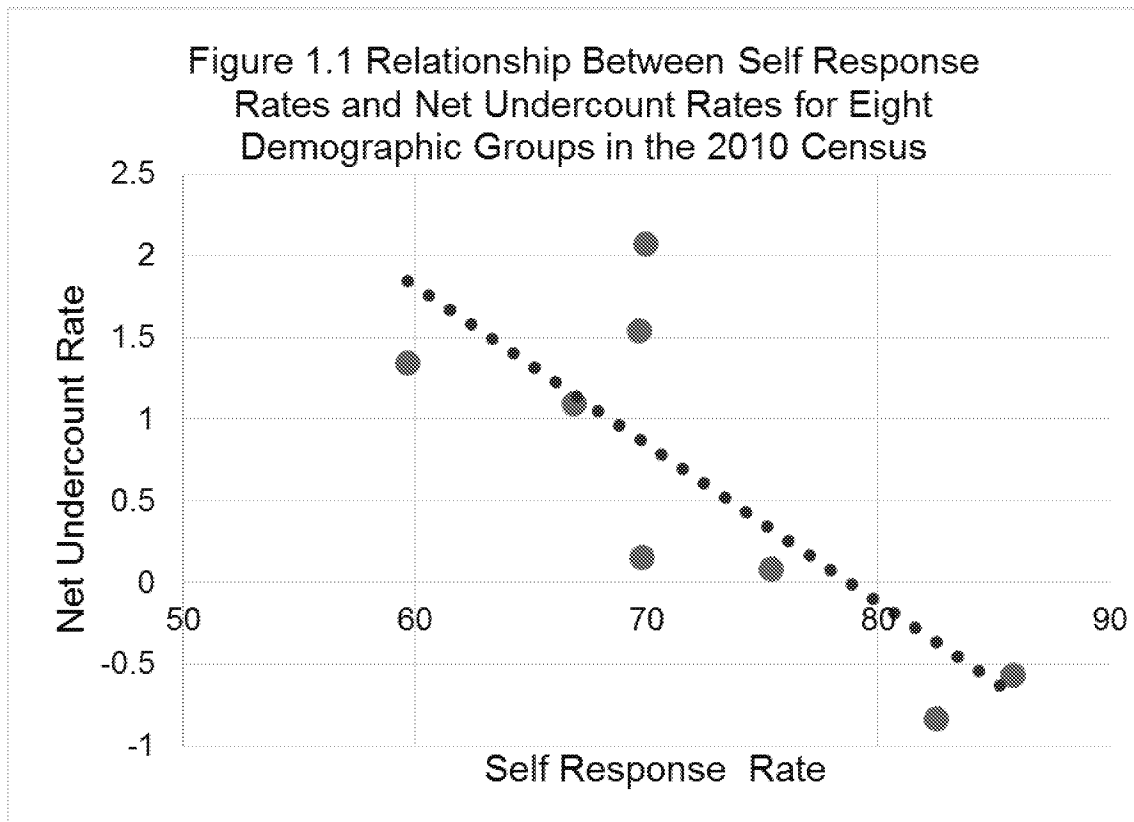
31. The correlation coefficient between the self-response rate and the net undercount rate for the eight groups shown in Table 1.1 is -0.78. This correlation is statistically significantly different than zero at a 90 percent confidence level. This correlation means groups with lower self-response rates have higher net undercount rates.

32. The data in Table 1.1 are very consistent. All the demographic groups that have higher than average self-response rates have net overcounts and all groups with lower than average self-response rates have net undercounts.⁶

⁶ Asians essentially have self-response rates the same as the total population and essentially have a net undercount rate of zero.

| Table 1.1 Self-Reponses Rates and Net Undercount Rates for Eight Demographic Groups in the 2010 Census | | |
|--|---|------------------------|
| | Self-Response Rates (Mail Return Rates*) | Net Undercount Rates** |
| Total | 79.3 | -0.01 |
| White Alone*** | 82.5 | -0.84 |
| Black Alone | 70.0 | 2.07 |
| American Indian and Alaskan Native Alone | 69.8 | 0.15 |
| Asian Alone | 75.4 | -0.08 |
| Native Hawaiian or Pacific Islander Alone | 59.7 | 1.34 |
| Hispanic | 69.7 | 1.54 |
| Population in Owner-Occupied Housing Units | 85.8 | -0.57 |
| Population in Renter- Occupied Housing Units | 66.9 | 1.09 |
| * Source; U.S. Census Bureau (2012) 2010 Census Mail Response/Return Rates Assessment Report. 2010 Census Planning Memorandum Series, No. 198, Tables 10 and 12 (Race groups are Non-Hispanic) | | |
| ** This is the net undercount as a percent of the population. Source: U.S. Census Bureau (2012) 2010 Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Persons in the United States. , DSSD 2010 CENSUS COVERAGE MEASUREMENT MEMORANDUM SERIES #2010-G-01 Tables 7 and 10 (Net Undercounts shown as a positive number) | | |
| *** for the Net Undercount Rates, this is Non-Hispanic White Alone | | |

33. The relationship is shown graphically in Figure 1.1. Figure 1.1 shows that groups with lower self-response rates have higher net undercount rates.



34. The red dotted line shown in Figure 1.1 (and all other figures) is the trend line that reflects the statistical relationship between the two measures shown in the Figure. The closer the points are to the line, the higher the correlation.

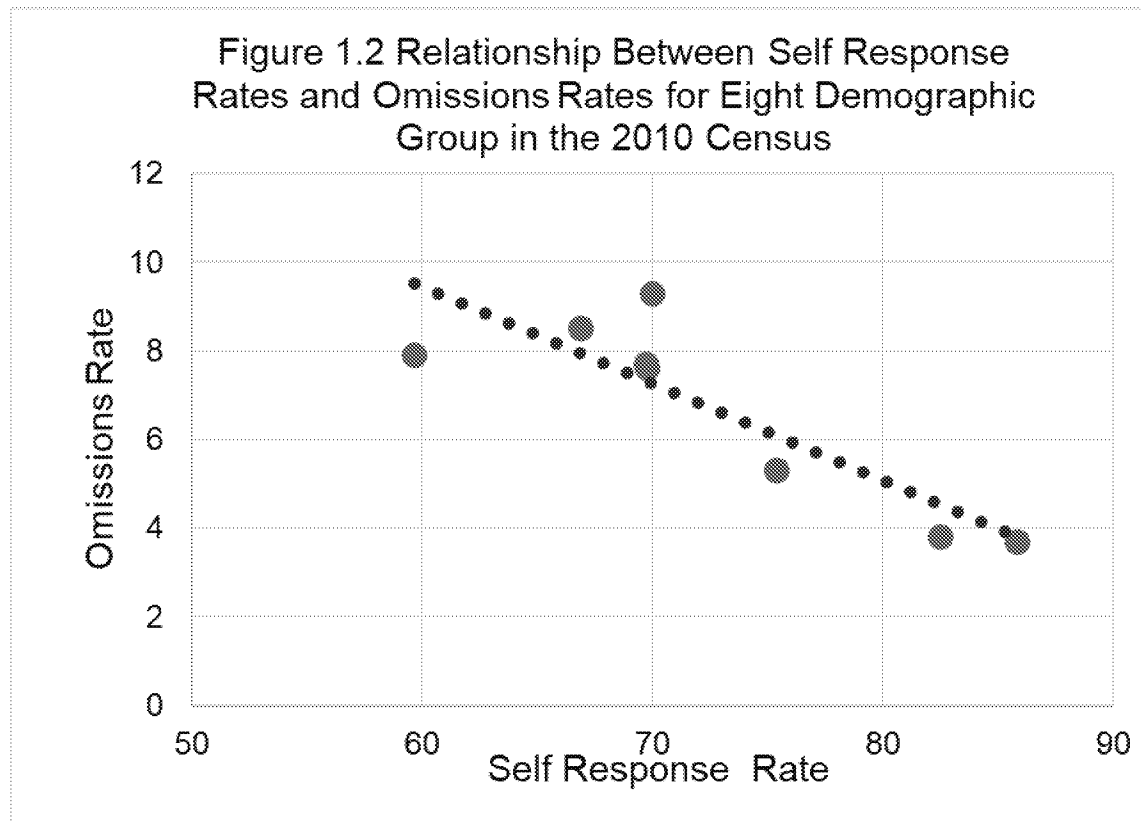
35. Table 1.2 shows 2010 Census self-response rates and omissions rates for the same eight demographic groups shown in Table 1.1. The correlation coefficient between the self-response rates and the omissions rates for the eight groups in Table 1.2 is -0.86 and it is statistically significantly different from zero at a 90 percent confidence level. The correlation means groups with lower self-response rates have higher omissions rates.

| Table 1.2 Self-Reponses Rates and Omission Rates for Demographic Groups in the 2010 Census | | |
|---|--|------------------|
| | Self-Response Rates (Mail Return Rates*) | Omission rates** |
| Total | 75.8 | 5.3 |
| White Alone*** | 82.5 | 3.8 |
| Black Alone | 70.0 | 9.3 |
| American Indian and Alaskan Native Alone | 69.8 | 7.6 |
| Asian Alone | 75.4 | 5.3 |
| Native Hawaiian or Pacific Islander Alone | 59.7 | 7.9 |
| Hispanic | 69.7 | 7.7 |
| Population in Owner-Occupied Housing Units | 85.8 | 3.7 |
| Population in Renter- Occupied Housing Units | 66.9 | 8.5 |
| * Source; U.S. Census Bureau (2012) 2010 Census Mail Response/Return Rates Assessment Report. 2010 Census Planning Memorandum Series, No. 198, Tables 10 and 12 | | |
| ** This is the number of people missed as a percent of the total population. Source: U.S. Census Bureau (2012) 2010 Components of Census Coverage for Race Groups and Hispanic Origin by Age, Sex and Tenure in the United States, DSSD 2010 CENSUS COVERAGE MEASUREMENT MEMORANDUM SERIES #2010-E-51, Tables A and B | | |
| *** for the Omissions Rates, this is Non-Hispanic White Alone | | |

36. All the groups that have a higher than average self-response rates have below average omissions rates and all the groups with lower than average self-response rates have higher than average omissions rates as shown in Table 1.2.⁷

37. The correlation can be seen graphically in Figure 1.2. This figure shows that groups with lower self-response rates have higher omissions rates.

⁷ Asians essentially have self-response rates that are the same as that total population and have an omissions rate exactly equal to the total population.



38. Table 1.3 shows the self-response rates and net undercount rates for states along with the District of Columbia. Note that none of the net undercount rates in Table 1.3 are statistically significantly different from zero (U.S. Census Bureau 2012c, Table 5). This indicates that the net undercount from state to state was roughly equal in 2010.

39. Given the lack of measurable variation in the state-level net undercount rates in the 2010 Census, correlation with self-response rates is expected to be low. Indeed, the correlation between self-response rates and net undercount rates across the states is 0.06, which is not statistically significantly different from zero. Given the low correlation between self-response rates and net undercount rates for states, the data are not shown graphically so there is no Figure 1.3.

| Table 1.3. 2010 Census Self-response Rates and Net Undercount Rates by State | | | | | |
|--|---|-----------------------|----------------|---|-----------------------|
| State | Self Response Rates (Mail Return Rate*) | Net Undercount Rate** | State | Self Response Rates (Mail Return Rate*) | Net Undercount Rate** |
| Alabama | 78.4 | 0.13 | Montana | 80.4 | -0.65 |
| Alaska | 74.8 | -0.85 | Nebraska | 82.5 | -0.54 |
| Arizona | 77.6 | -0.42 | Nevada | 76.3 | -0.04 |
| Arkansas | 77.0 | -0.41 | New Hampshire | 79.4 | 0.6 |
| California | 76.9 | 0.26 | New Jersey | 78.1 | -0.36 |
| Colorado | 79.1 | -0.29 | New Mexico | 73.8 | -0.16 |
| Connecticut | 79.1 | -0.45 | New York | 75.8 | -0.79 |
| Delaware | 80.0 | 0.55 | North Carolina | 80.7 | 0.52 |
| District of Columbia | 78.3 | 2.23 | North Dakota | 83.1 | 0.09 |
| Florida | 80.2 | 0.45 | Ohio | 80.8 | -0.83 |
| Georgia | 77.2 | 0.91 | Oklahoma | 75.5 | -1.08 |
| Hawaii | 76.8 | -0.44 | Oregon | 79.8 | 0.02 |
| Idaho | 82.6 | -0.03 | Pennsylvania | 82.3 | 0.14 |
| Illinois | 80.7 | -0.48 | Rhode Island | 77.7 | -0.81 |
| Indiana | 82.2 | -0.67 | South Carolina | 81.4 | 0.41 |
| Iowa | 83.3 | -0.28 | South Dakota | 82.7 | 0.1 |
| Kansas | 81.2 | -0.67 | Tennessee | 80.3 | 0.12 |
| Kentucky | 81.0 | -0.13 | Texas | 76.5 | 0.97 |
| Louisiana | 74.5 | -0.38 | Utah | 80.4 | -0.48 |
| Maine | 81.1 | 0.65 | Vermont | 79.7 | 1.29 |
| Maryland | 80.3 | 0.94 | Virginia | 80.8 | 0.57 |
| Massachusetts | 78.9 | -0.52 | Washington | 79.9 | -0.1 |
| Michigan | 83.7 | -0.66 | West Virginia | 75.6 | -1.43 |
| Minnesota | 85.6 | -0.56 | Wisconsin | 85.1 | -0.17 |
| Mississippi | 76.4 | 0.24 | Wyoming | 79.9 | -0.51 |
| Missouri | 81.1 | -0.66 | Total | 79.3 | -0.01 |

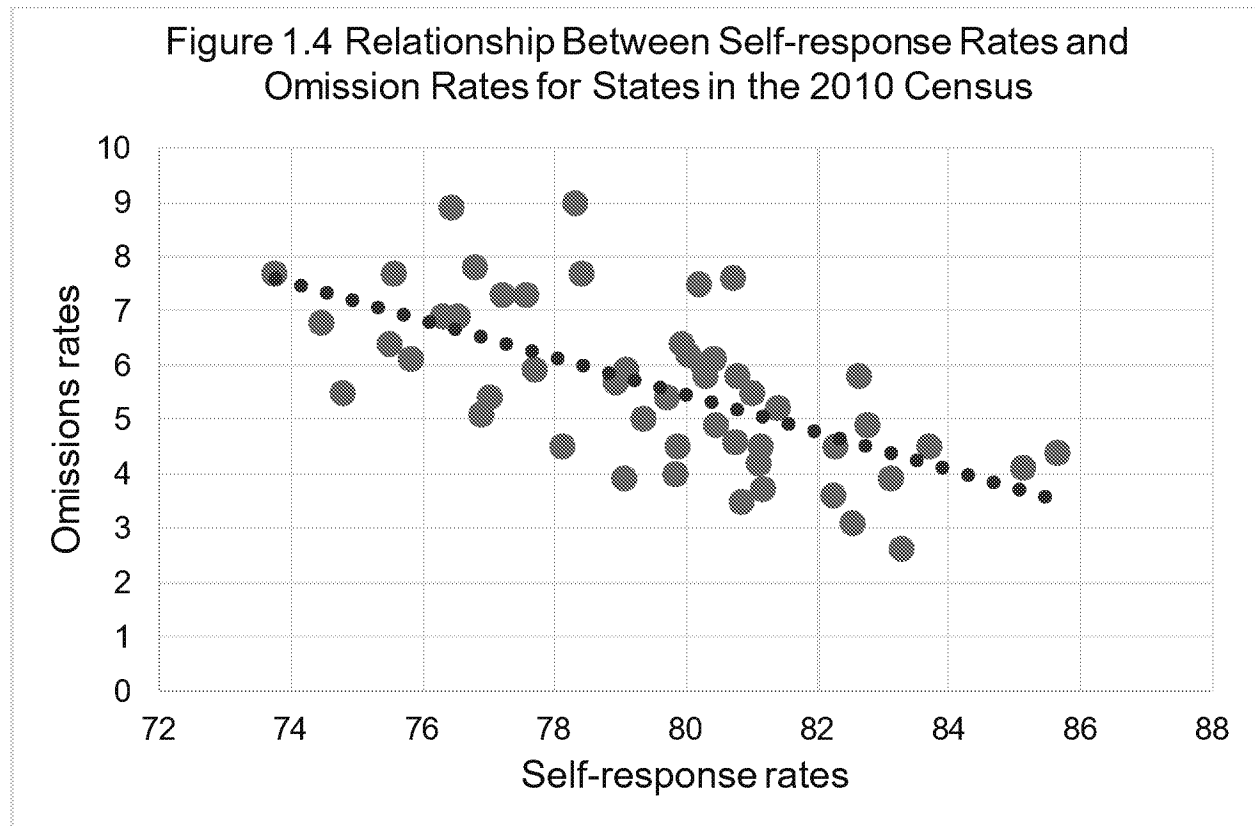
* Source: U.S. Census Bureau, State Mail Return Rates 2010 Census downloaded on August 21 at https://www2.census.gov/dssd/2010_census_public_rates/excel/

** Net undercount as a percent of the total population. Source: U.S. Census Bureau (2012). "2010 Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Persons in the United States," DSSD 2010 Census Coverage Measurement Memorandum Series #2010-G-01. U.S. Census Bureau, Washington, DC. G-01 Table 14 (Net undercounts are shown as a positive number)

40. Table 1.4 shows self-response rates and omissions rates for states and the District of Columbia in the 2010 Census. The correlation between self-response rates and omissions rates is -0.63, and it is statistically significantly different from zero at a 90 percent confidence level. States that have lower self-response rates have higher omissions rates.

| Table 1.4. 2010 Census Self-response Rates and Omissions Rates by State | | | | | |
|---|---|------------------|----------------|---|------------------|
| State | Self Response Rates (Mail Return Rate*) | Omissions Rate** | State | Self Response Rates (Mail Return Rate*) | Omissions Rate** |
| Alabama | 78.4 | 7.7 | Montana | 80.4 | 6.1 |
| Alaska | 74.8 | 5.5 | Nebraska | 82.5 | 3.1 |
| Arizona | 77.6 | 7.3 | Nevada | 76.3 | 6.9 |
| Arkansas | 77.0 | 5.4 | New Hampshire | 79.4 | 5.0 |
| California | 76.9 | 5.1 | New Jersey | 78.1 | 4.5 |
| Colorado | 79.1 | 5.9 | New Mexico | 73.8 | 7.7 |
| Connecticut | 79.1 | 3.9 | New York | 75.8 | 6.1 |
| Delaware | 80.0 | 6.2 | North Carolina | 80.7 | 7.6 |
| District of Columbia | 78.3 | 9.0 | North Dakota | 83.1 | 3.9 |
| Florida | 80.2 | 7.5 | Ohio | 80.8 | 3.5 |
| Georgia | 77.2 | 7.3 | Oklahoma | 75.5 | 6.4 |
| Hawaii | 76.8 | 7.8 | Oregon | 79.8 | 4.0 |
| Idaho | 82.6 | 5.8 | Pennsylvania | 82.3 | 4.5 |
| Illinois | 80.7 | 4.6 | Rhode Island | 77.7 | 5.9 |
| Indiana | 82.2 | 3.6 | South Carolina | 81.4 | 5.2 |
| Iowa | 83.3 | 2.6 | South Dakota | 82.7 | 4.9 |
| Kansas | 81.2 | 3.7 | Tennessee | 80.3 | 5.8 |
| Kentucky | 81.0 | 5.5 | Texas | 76.5 | 6.9 |
| Louisiana | 74.5 | 6.8 | Utah | 80.4 | 4.9 |
| Maine | 81.1 | 4.2 | Vermont | 79.7 | 5.4 |
| Maryland | 80.3 | 6.0 | Virginia | 80.8 | 5.8 |
| Massachusetts | 78.9 | 5.7 | Washington | 79.9 | 4.5 |
| Michigan | 83.7 | 4.5 | West Virginia | 75.6 | 7.7 |
| Minnesota | 85.6 | 4.4 | Wisconsin | 85.1 | 4.1 |
| Mississippi | 76.4 | 8.9 | Wyoming | 79.9 | 6.4 |
| Missouri | 81.1 | 4.5 | Total | 79.3 | 5.3 |
| * Source: U.S. Census Bureau, State Mail Return Rates 2010 Census downloaded on August 21 at https://www2.census.gov/dssd/2010_census_public_rates/excel/ | | | | | |
| ** Number of people missed as a percent of total population. Source: U.S. Census Bureau (2012). "2010 Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Persons in the United States," DSSD 2010 Census Coverage Measurement Memorandum Series #2010-G-01. U.S. Census Bureau, Washington, DC. G-01 Table 14 (Net undercounts are shown as a positive number) | | | | | |

41. Figure 1.4 shows the relationship between self-response rates and omissions rates for states in the 2010 Census graphically. Figure 1.4 shows that states with lower self-response rates have higher omissions rates.



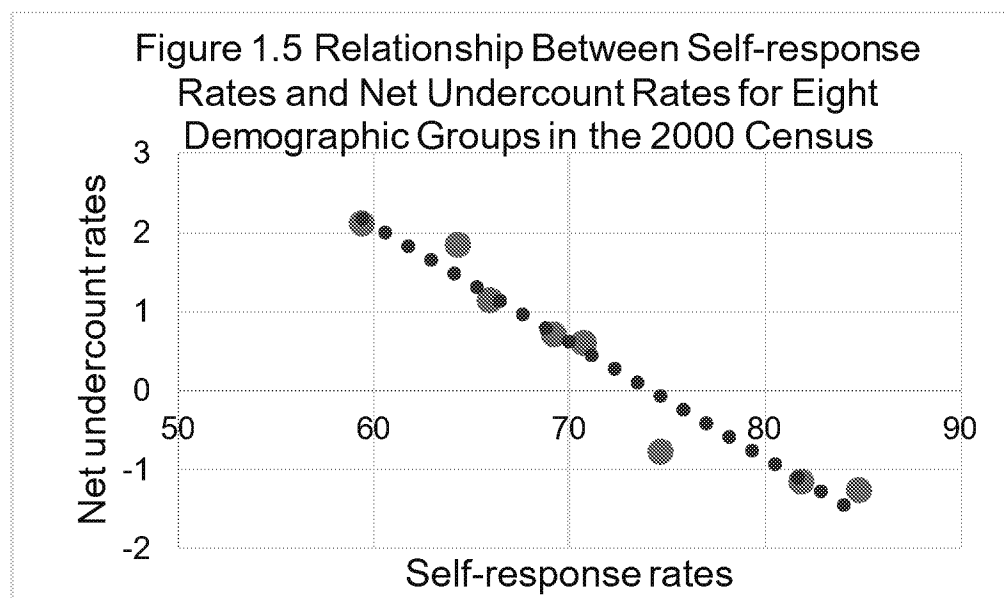
1.2.2 Examination of Data from the 2000 Census

42. Table 1.5 shows self-response rates and net undercount rates from the 2000 Census for eight demographic groups. Note that the racial groups are not defined exactly the same in the two Census Bureau reports from which the data were taken but they are very similar. This is a minor point and unlikely to impact the correlation.

43. The correlation coefficient between self-response rates and net undercount rates in Table 1.5 is -0.97, which is extremely high and statistically significantly different from zero at a 90 percent confidence level. This means that demographic groups that have low self-response rates have high net undercount rates.

| Table 1.5 Self-Response Rates and Net Undercount Rates in the 2000 Census for Eight Demographic Groups | | | |
|--|--|------------------------------|---|
| Groups | Self Response Rates (Mail Return Rate)* | Groups | Net Undercount Rates (A.C.E. Revision II)** |
| White Alone | 81.8 | Non-Hispanic White | -1.13 |
| Black Alone | 64.3 | Non-Hispanic Black | 1.84 |
| Asian Alone | 74.6 | non-Hispanic Asian | -0.75 |
| Pacific Islander Alone | 59.4 | Hawaiian or Pacific Islander | 2.12 |
| Hispanic | 69.2 | Hispanic | 0.71 |
| American Indian Alone | 70.7 | AIAN Off Reservations | 0.62 |
| Owner-Occupied | 84.8 | Homeowner | -1.25 |
| Renter-Occupied | 65.9 | Renter | 1.14 |
| <p>* Source: U.S. Census Bureau (2003) Census 2000 Mail Return Rates, Census 2000 Evaluation A.7.b, Herbert Stackhouse and Sarah Brady, January 30, Tables 10 , 12 and 16</p> <p>**Source: Net undercount as a percent of the total population.U.S. Census Bureau : DSSD A.C.E. REVISION II MEMORANDUM SERIES #PP-54, Table 1. (Net undercounts are shown as positive numbers)</p> | | | |

44. The relationship between self-response rates and net undercount rates is shown graphically in Figure 1.5. This figure shows that groups that have lower self-response rates have higher net undercount rates.



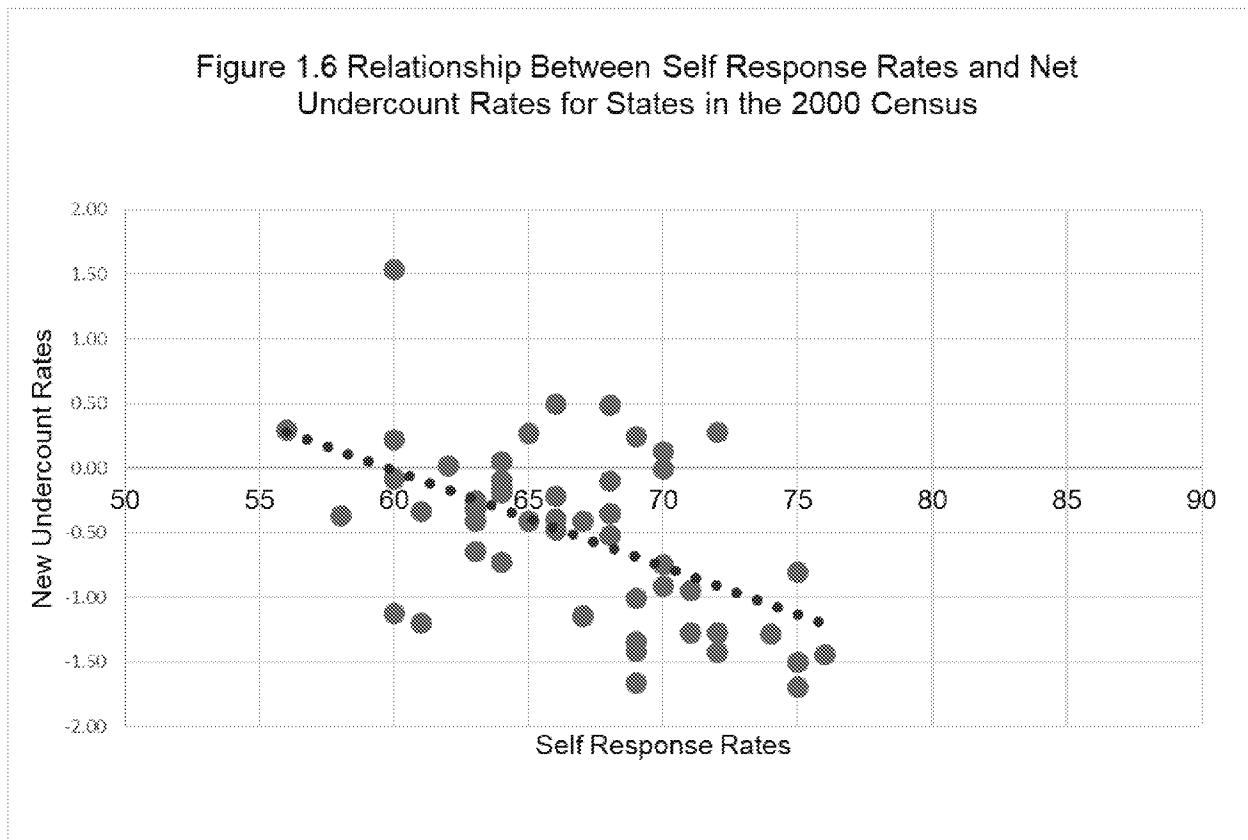
45. Table 1.6 shows the self-response rates and net undercount rates for states and the District of Columbia in the 2000 Census. State omissions rates were not available in 2000. The correlation between self-response rates and net undercount rates across the states is -0.66, which is statistically significantly different from zero at a 90 percent confidence level. States with low self-response rates have high net undercount rates.

| Table 1.6 Census 2000 Self-Response Rates and Undercount Rates for States | | | | | | |
|---|--|------------------------|--|----------------|------------------------------|----------------------|
| State | Self-Response Rates (Mail Return Rates)* | Net Undercount Rates** | | State | Response Rates (Mail Return) | Net Undercount Rates |
| Alabama | 76.9 | -0.34 | | Montana | 83.2 | 0.49 |
| Alaska | 76.1 | 0.29 | | Nebraska | 84.6 | -0.81 |
| Arizona | 76.9 | -0.32 | | Nevada | 75.0 | 0.50 |
| Arkansas | 79.0 | -0.09 | | New Hampshire | 80.5 | -1.15 |
| California | 78.6 | 0.13 | | New Jersey | 78.7 | -0.52 |
| Colorado | 80.8 | -0.01 | | New Mexico | 78.1 | 0.02 |
| Connecticut | 80.2 | -0.75 | | New York | 75.2 | -0.25 |
| Delaware | 78.0 | -0.32 | | North Carolina | 78.3 | -0.15 |
| District of Columbia | 72.1 | 1.54 | | North Dakota | 85.4 | -1.43 |
| Florida | 77.8 | -0.64 | | Ohio | 82.1 | -1.27 |
| Georgia | 79.1 | 0.27 | | Oklahoma | 77.9 | -0.20 |
| Hawaii | 75.7 | 0.22 | | Oregon | 81.1 | -0.35 |
| Idaho | 83.5 | -0.41 | | Pennsylvania | 82.4 | -0.91 |
| Illinois | 80.2 | -1.42 | | Rhode Island | 76.9 | -1.14 |
| Indiana | 81.6 | -1.66 | | South Carolina | 76.5 | -0.36 |
| Iowa | 85.6 | -1.44 | | South Dakota | 86.8 | -1.28 |
| Kansas | 81.8 | -1.28 | | Tennessee | 77.1 | -0.41 |
| Kentucky | 79.9 | -0.48 | | Texas | 75.3 | 0.05 |
| Louisiana | 75.2 | -0.09 | | Utah | 79.6 | -0.10 |
| Maine | 80.1 | -1.20 | | Vermont | 81.1 | -1.12 |
| Maryland | 79.3 | 0.25 | | Virginia | 81.3 | 0.27 |
| Massachusetts | 79.0 | -1.00 | | Washington | 78.6 | -0.21 |
| Michigan | 83.7 | -0.95 | | West Virginia | 80.7 | -0.73 |
| Minnesota | 86.1 | -1.70 | | Wisconsin | 87.3 | -1.50 |
| Mississippi | 78.3 | -0.41 | | Wyoming | 83.6 | -0.39 |
| Missouri | 82.2 | -1.35 | | United States | 78.4 | 0.48 |

* Source: U.S. Census Bureau, State Mail Return Rates 2010 Census downloaded on August 21 at https://www.2.census.gov/dssd/2010_census_public_rates/excel/

** Net undercount as a percent of the total population. Source: U.S. Census Bureau (2003) A.C.E. Revision II- Adjusted Data for States, Counties, and Places, DSSD A.C.E. REVISION II MEMORANDUM SERIES #PP 60, Table 1 (Net Undercounts Shown as a positive number)

46. This relationship is shown graphically in Figure 1.6. This figure shows that states that have lower self-response rates have higher net undercount rates.



1.2.3. Examination of Data from the 1990 Census

47. The only self-response rates available for states in the 1990 Census were mail response rates. Mail response rates are slightly different than the mail return rates (as explained in Section 1.1), but both are measures of self-response used by the Census Bureau.

48. Table 1.7 shows self-response rates and net undercount rates in the 1990 Census for seven demographic groups. The correlation between the self-response rates and the net undercount rates is -0.60, which is statistically significantly different from zero at a 90 percent confidence level. The direction of the correlation indicates that groups with lower self-response rates have higher net undercount rates.

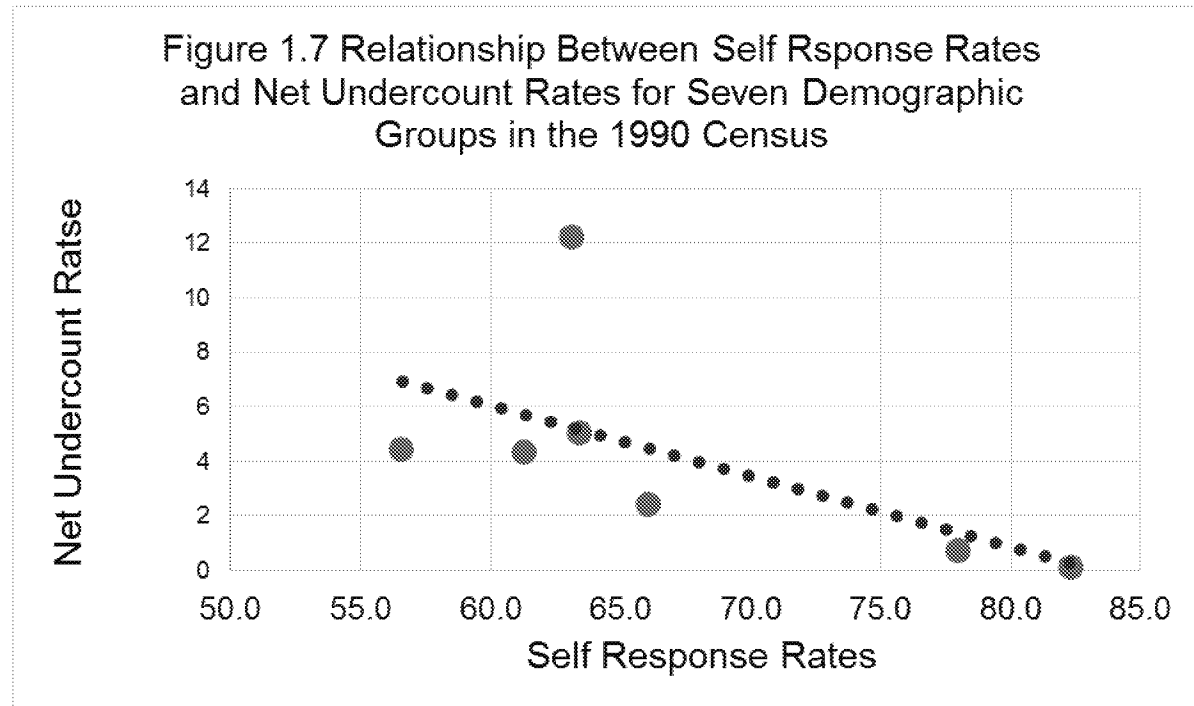
Table 1.7 1990 Census Self Response Rates and Net Undercount Rates for Seven Demographic Groups

| | Self Response Rates (Mail Responses Rates)* | | Net Undercount Rate ** |
|------------------------------------|---|-----------------------------------|------------------------|
| Non-Hispanic White | 78.0 | Non-Hispanic White | 0.7 |
| Black | 56.6 | Black | 4.4 |
| American Indians, Eskimo and Aleut | 63.1 | American Indian, Eskimo and Aleut | 12.2 |
| Asian and Pacific Islanders | 66.1 | Asians and Pacific Islander | 2.4 |
| Hispanic Origin | 63.4 | Hispanic Origin | 5.0 |
| Owners | 82.3 | Owners | 0.1 |
| Renters | 61.3 | Renters | 4.3 |

*Source: Derived from Word, D.L., (1997) "Who Responds ? Who Doesn't?: Analyzing Variation in Mail Response Rates During the 1990 Census, Population Division Working Paper No . 19, Table 2.0

**Net undercount as a percent of the total population. Source: Hogan, H. and Robinson G., (1993) What the Census Bureau's Coverage Evaluation Programs tell Us About Differential Undercounts ; Paper Delivered at the 1993 Research Conference on Undercounted Ethnic Populations, May 5-7, Richmond VA. , Table 3 (net undercounts shown as a positive number)

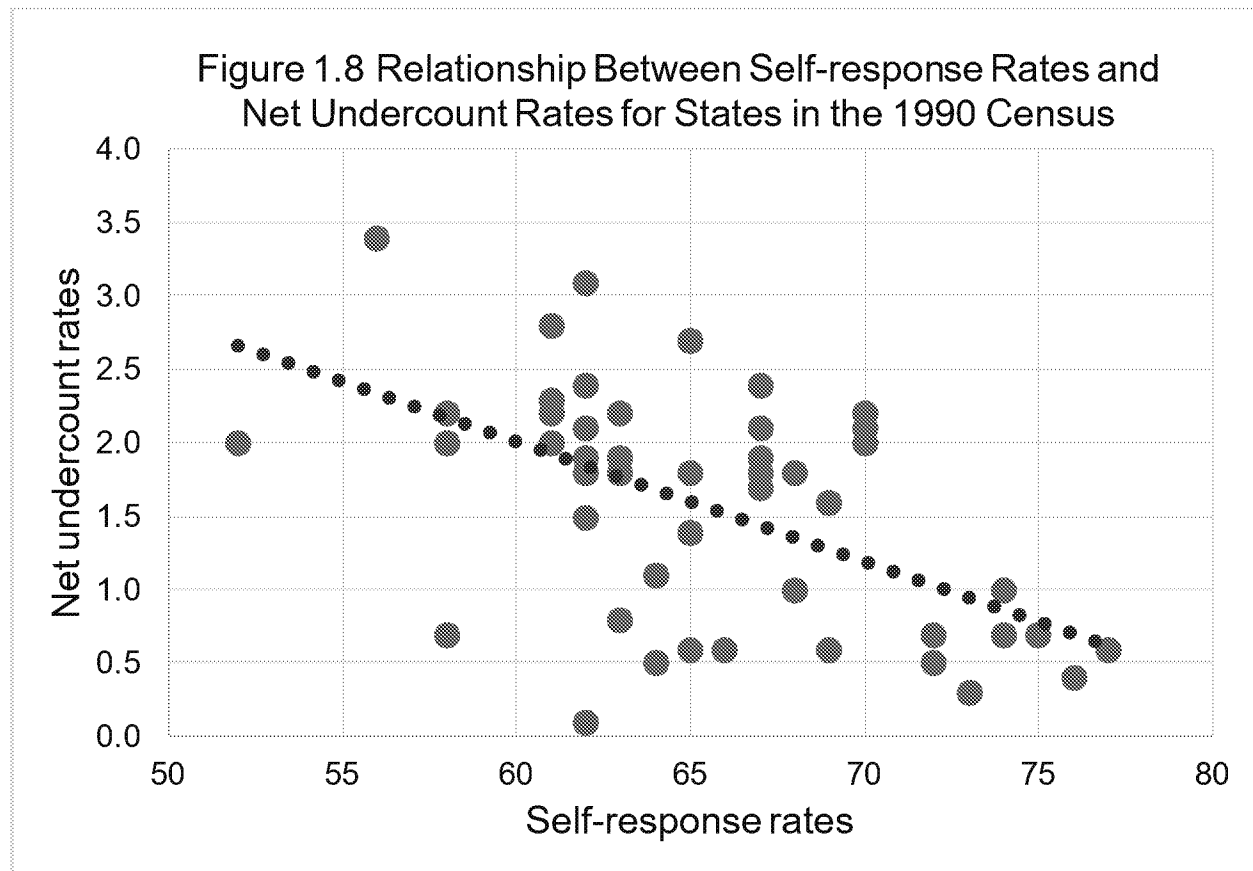
49. This relationship is shown graphically in Figure 1.7. This figure shows that groups that have low self-response rates have higher net undercount rates.



50. Table 1.8 shows 1990 Census self-response rates and net undercount rates for states and the District of Columbia. Omissions rates were not available in 1990. The correlation coefficient between self-response rates and net undercount rates, shown in Table 1.8, is -0.56, which is statistically significantly different from zero at a 90 percent confidence level. This means that states with lower self-response rates have higher net undercount rates.

| Table 1.8 1990 Census Self-response Rates and Net Undercount Rates for States | | | | | |
|---|--|----------------------------------|----------------|--|----------------------------------|
| state | Self Response Rates (Mail Response Rates)* | 1990 Net Undercount of Persons** | state | Self Response Rates (Mail Response Rates)* | 1990 Net Undercount of Persons** |
| Alabama | 62.0 | 1.8 | Montana | 67.0 | 2.4 |
| Alaska | 52.0 | 2.0 | Nebraska | 74.0 | 0.7 |
| Arizona | 62.0 | 2.4 | Nevada | 61.0 | 2.3 |
| Arkansas | 65.0 | 1.8 | New Hampshire | 63.0 | 0.8 |
| California | 65.0 | 2.7 | New Jersey | 65.0 | 0.6 |
| Colorado | 67.0 | 2.1 | New Mexico | 62.0 | 3.1 |
| Connecticut | 66.0 | 0.6 | New York | 62.0 | 1.5 |
| Delaware | 68.0 | 1.8 | North Carolina | 63.0 | 1.9 |
| District of Columbia | 56.0 | 3.4 | North Dakota | 72.0 | 0.7 |
| Florida | 61.0 | 2.0 | Ohio | 75.0 | 0.7 |
| Georgia | 63.0 | 2.2 | Oklahoma | 63.0 | 1.8 |
| Hawaii | 62.0 | 1.9 | Oregon | 67.0 | 1.9 |
| Idaho | 70.0 | 2.2 | Pennsylvania | 73.0 | 0.3 |
| Illinois | 68.0 | 1.0 | Rhode Island | 62.0 | 0.1 |
| Indiana | 72.0 | 0.5 | South Carolina | 58.0 | 2.0 |
| Iowa | 76.0 | 0.4 | South Dakota | 74.0 | 1.0 |
| Kansas | 72.0 | 0.7 | Tennessee | 65.0 | 1.8 |
| Kentucky | 69.0 | 1.6 | Texas | 61.0 | 2.8 |
| Louisiana | 58.0 | 2.2 | Utah | 67.0 | 1.7 |
| Maine | 58.0 | 0.7 | Vermont | 64.0 | 1.1 |
| Maryland | 70.0 | 2.1 | Virginia | 70.0 | 2.0 |
| Massachusetts | 64.0 | 0.5 | Washington | 67.0 | 1.8 |
| Michigan | 72.0 | 0.7 | West Virginia | 65.0 | 1.4 |
| Minnesota | 76.0 | 0.4 | Wisconsin | 77.0 | 0.6 |
| Mississippi | 62.0 | 2.1 | Wyoming | 61.0 | 2.2 |
| Missouri | 69.0 | 0.6 | U.S. Total | | 1.6 |
| * Source: U.S. Census Bureau 1990 Census Page (/main/www.cen1990.html) 1990 Mail Response rates by 1990 Geography Boundaries. | | | | | |
| **Net undercount as a percent of the total population. Source: U.S. Census Bureau https://www.census.gov/dmd/www/pdf/understate.pdf (Net undercount shown as a positive number) | | | | | |

51. Figure 1.8 shows the relationship between state 1990 mail response rates and net undercount rates graphically. This figure shows that states that have lower self-response rates have higher net undercount rates.



1.2.4 Summary of Relationship between Self-response Rates and Census Accuracy.

52. Table 1.9 summarizes the correlations between self-response rates and census accuracy for the 1990, 2000 and 2010 Decennial Censuses. Of the eight correlations shown in Table 1.9, all but one of the correlations were in the predicted direction and statistically significant. Based on my 40 plus years of experience as a professional data analyst I would call the correlations coefficients in Table 1.9 (except for 0.06) moderate to high by social science standards.

| Table 1.9 Summary of Statistical Relationships between Census Self-Response Rates and Census Accuracy (Net Undercount Rates and Omissions Rates) | |
|--|-------------------------|
| Correlation between Self-Response Rates and: | Correlation Coefficient |
| 2010 Eight Demographic Groups Net Undercount | -0.78 |
| 2010 Eight Demographic Groups Omissions | -0.86 |
| 2010 States Net Undercount Rates | 0.06 |
| 2010 States Omissions Rates | -0.63 |
| 2000 Eight Demographic Groups | -0.97 |
| 2000 States Net Undercount Rates | -0.66 |
| 1990 Seven Demographic Groups | -0.61 |
| 1990 States Net Undercount Rates | -0.56 |
| Note correlations in BOLD are statistically significant at the .10 level or higher. | |
| | |

53. Using this analysis to predict the exact increase in net undercounts and omissions based on self-response rates would depend on which correlation in Table 1.9 one relies on. But exact predictions are unnecessary. The preponderance of evidence clearly shows there will be an increase in net undercounts and omissions if there are lower self-response rates in the 2020 Census. The magnitude of the correlations varies from one Census to the next, but they are consistent in showing a negative correlation between self-response rates and census accuracy, which means states and groups with lower self-response rates have higher net undercounts and omission rates.

54. The empirical relationship between self-response rates and census accuracy (net undercounts and omissions) has been recognized by the Census Bureau. The Census Bureau Task Force on the Undercount of Young Children (U.S. Census Bureau 2014a, page ii) concluded, “Research suggests that areas with lowest levels of cooperation have higher levels of coverage and nonresponse error.” A Census Bureau Working Paper (Word 1997, page 1) notes that “response rates and net undercount rates may be causally linked . . .”

55. The connection between self-response rates and census accuracy is underscored by the Census Bureau’s decision to use a self-response related measure to identify Hard-to-Count areas in the 2020 Census. The Low-Response Score developed by Erdman and Bates (2017) is based on the mail return rates in the 2010 Census. In describing the Low-Response Score the Census Bureau (2014b, page 4) states, “This score identifies Block Groups and Tracts whose characteristics predict low Census Mail Return Rate and are highly correlated (negatively) with Census and survey participation.” The implicit association here is that areas where self-response rates are low are more difficult to enumerate. Several characteristics of the kinds of populations and places where it is difficult to get an accurate enumeration are provided by O’Hare (2019a, page 46). This is not a complete list, but some of the characteristics include racial and ethnic minority populations, communities where there are high levels of poverty and unemployment, high levels of renter households and multi-unit structures, and large numbers of undocumented or recent immigrants.

56. It is easy to understand why the relationship between low self-response rates and lower census accuracy exists. Households that do not self-respond end up in the non-response followup (NFRU) universe where the Census Bureau must send out an enumerator to get information from a nonresponding household. Data collected in the NFRU phase of the Census

is more likely to omit a person than data gathered in the self-response phase. In the 2010 Census, 88 percent of the NRFU responses were correct, compared to 97 percent of self-responses (author's calculation from U.S. Census Bureau 2012b, Table 14).

57. In addition, NRFU responses may have to rely on a proxy response. A proxy response is when the information for a housing unit is provided by someone not living in that housing unit, such as a neighbor or landlord. A U.S. Census Bureau paper (2018d, page 42) shows that the responses from the self-response portion of the Census are much more accurate than responses from the NRFU proxy response portion (U.S. Census Bureau 2018d, Table 12). This data showed that 97.3 percent of the responses from the Mailout/Mail back portion of the Census were correct, as compared to just 70.2 percent of those from the NRFU proxy responses. Some of the NRFU proxy response errors are people who are not counted in the Census when they should have been counted.

58. Social scientists typically look for four elements to show causation. First, that the causal agent (referred to as the independent variable by scientists) occurs prior in time to the thing that it is causing (referred to as the dependent variable by scientists); second, that there is an association or correlation between the causal agent and the thing being caused; third, that intervening mechanisms linking the independent variable and the dependent variable can be clearly specified; and finally that other potential explanations have been controlled.

59. My analysis satisfies three out of four of these elements. Self-response occurs prior in time to net undercounting, the self-response rate is moderately to highly correlated with net undercounting, and the intervening mechanism is the fact that groups with lower self-response rates have a higher share of their population counted in the NRFU operation which generates less accurate data, including higher rates of net undercounts and omissions. The only

element my analysis does not address is the need to control for all other potential explanations. The inability to control for all other potential explanations is common in social science research because there are legal and ethical restrictions on how much people can be manipulated for research purposes. The way to control for all other possible explanations is through a randomized control trial (“RCT”). However, the Census Bureau, which is best positioned to conduct an RCT, has not conducted any such RCT measuring the relationship between self-response and undercounting. My analysis evaluates the relationship between self-response rates and census accuracy with best available data, and shows there is a strong robust relationship between self-response and Census accuracy; namely groups that have lower self-response rates have higher net undercount and omissions rates.

60. The magnitude of the correlations varies from one Census to the next, but they are consistent in showing a negative correlation between self-response rates and census accuracy, which means states and groups with lower self-response rates have higher net undercounts and omission rates.

61. The consistency of the correlation (7 out of 8 observations) across multiple Censuses, demographic groups, and states is illustrative of a consistent relationship over time. The analysis demonstrates a clear pattern in the relationship between self-response and undercount rates. While there is some uncertainty in these data (as with all data), uncertainty typically reduces the likelihood of finding a correlation. But here, my analysis demonstrates a correlation despite measurement uncertainty, providing further proof that the relationship is real.

62. The empirical relationship between self-participation rates and census accuracy has been recognized by the Courts. *See New York v. Dep’t of Commerce*, 351 F.Supp.3d 502, 591 (S.D.N.Y. 2019) (“The Court concludes just that: Dr. O’Hare’s testimony provides

affirmative evidence that self-response declines among specific subpopulations directly cause net undercounts of those subpopulations. For the purposes of this litigation, a preponderance of the evidence supports that conclusion.”); *see also Kravitz v. Dep’t of Commerce*, 366 F.Supp.3d 681, 717 (D.Md. 2019) (“Thus, the Court is comfortable finding that Plaintiffs have demonstrated a causal relationship between decreased Census participation and an increased likelihood of net undercounting by a preponderance of the evidence.”).

63. It is my conclusion, that over the past several U.S. Censuses the empirical evidence shows groups with lower self-response rates have higher net undercounts and omission rates. This relationship is important in understanding the significance of self-response rates in the 2020 Census. Furthermore, groups with lower self-response rates in the 2020 Census would benefit disproportionately if the end of the data collection period was October 31, 2020 instead of September 30, 2020, as the Census Bureau had planned a couple of months ago. Conversely, truncation of the data collection period in the 2020 Census will result in greater omissions and net undercounts in groups with lower self-response rates.

2) Self-Reporting Rates in the 2020 Census Indicate Same Patterns as the Past

64. In the following sections, I focus on differences between the largest racial and ethnic minority groups (Hispanics, Blacks, and Asians) in comparison to Whites and Non-Hispanic Whites. These are the groups for which the data are most reliable. States also show wide variations in self-response rates based on currently available data, explained below.

65. The primary measures of 2020 census accuracy (net undercounts and omissions) will not be available until 2021. One metric of census quality that is available now is self-response rates (O’Hare et al. 2020). Self-response rates reflect the extent to which households complete and return the Census questionnaires before they are visited by a census enumerator in

the NRFU operation. In the 2010 Census, when mailing back a completed census questionnaire was the only option for self-response, these were called mail return rates. In the 2020 Census, the self-response could be online, by phone, or by mail.

66. The predictive value of self-response rates was shown in the previous section where empirical evidence linked variations in self-response rates for groups with variations in census accuracy for those groups; namely groups with low self-response rates have higher net undercount and omissions rates.

67. Other demographers have also noted the importance of self-response rates. In the context of the U. S. Census, Swanson (2019, page 6) indicates self-response rates are a key indicator of census success. New York City Demographer Joe Salvo (2020, page 1) also links self-response rates to Census accuracy when he states, “If an area has a low self-response rate, it means:

- More census enumerators will need to knock on doors to count residents in persons: and,
- It is more likely people in the area may be missed or counted inaccurately.”

68. In the 2010 Census, the Census Bureau stopped soliciting self-responses when it started the Nonresponse Followup (NRFU) operation in early May. For the 2020 Census, the Census Bureau is continuing to allow people to self-respond during the NRFU period. However, most of the 2020 Census self-response data shown here is from the 2020 Census data collection period prior to the start of the NRFU operation in early August.

69. Since March 20, 2020, the Census Bureau has been producing 2020 Census self-response rates for many geographic areas including census tracts (U.S. Census Bureau 2020a). A census tract is defined by the Census Bureau (2020b) as “small, relatively permanent statistical

subdivisions of a county,” each with a unique numeric code, and an average of about 4,000 inhabitants, but between a minimum population of 1,200 and maximum population of 8,000. In the 2020 Census there are about 84,000 census tracts in the country.

70. At this point in the 2020 Census cycle there are no publicly available data on self-response rates by the race or Hispanic Origin of the householder but response rates have been developed related to the race and Hispanic composition of census tracts. The staff at Center for Urban Research at the Graduate Center, City University of New York (CUNY) have downloaded and analyzed response rates provided by the Census Bureau and combined them with other information from the Census Bureau about the racial and Hispanic composition of the census tract. Through regular briefings they have made analysis of that information available to the public (Census Funders Initiative 2020).

71. Staff at the Center for Urban Research at the Graduate Center, City University of New York determined the plurality of the population in each census tract by race and Hispanic Origin.⁸ The plurality of the population in a census tract is the largest race or Hispanic Origin population in the census tract.⁹

72. The racial compositions of populations in the tracts are based on the U.S. Census Bureau’s 2014-2018 American Community Survey (ACS). Since the ACS data are produced from a sample of the population, they include sampling error. ACS sampling error for individual tracts indicate large potential errors for these estimates, but when tracts are used collectively, like they are here, sample error is minimal. This is the best data we currently have for calculating the racial/Hispanic composition of the Census tracts in the 2020 Census.

⁸ A small number of census tracts, where were less than 100 people, were not included.

⁹ If one used only tracts where a single race or Hispanic Origin group were the majority rather than the plurality, it would greatly limit the number of tracts available for analysis. By using the plurality, nearly every census tract in the country is included in the analysis.

73. Race and Hispanic Origin are measured in the U.S. Census as dictated by U.S. Office of Management and Budget (1997). Race and Hispanic Origin are two separate concepts in the definitions used by the federal government. In the Census, respondents are first asked if they are Hispanic or not, then they are asked about what race group(s) they identify with. Starting in 1997, people have been allowed to mark as many race groups as they feel apply. For people who mark only one race, this is referred to as “race alone,” for example Black Alone or Asian Alone. For people who mark more than one race they fall into categories labeled “Alone or in Combination” for example, “Black Alone or in Combination.” In this construction, people can be in more than one group. Someone who marked both Black and White would be included in both Black alone or in combination and the White alone or in combination. Slightly different racial definitions are used in different tables in this report based on what was made available by the Census Bureau. For example, sometimes the Census Bureau reports data for Non-Hispanic White population and sometimes for the White population.

74. In general, these differences are not particularly important in terms of understanding the results of my analysis, but there are couple of clarifications I want to offer. The way the Census Bureau classifies people by race and Hispanic Origin has two key implications for the data reported in the next three sections. Sometimes data were available for all the people who selected the “White” race and sometimes the data was available for Non-Hispanic Whites. Since some Hispanics select the White race, data for all Whites includes some Hispanics. Using data for Non-Hispanic Whites in comparison to minorities is preferable to using data for Whites, but sometimes that was not possible. The distinction between race alone and race alone or in combination is of little significance for the racial groups analyzed here (White, Asian, and Black).

75. Analysis of 2020 Census self-response rates through August 2020 indicates that many of the self-participation patterns from past Censuses are being seen again in the 2020 Census. This suggests that differential census accuracy in the 2020 Census is likely to follow patterns seen in the past censuses and that groups with low self-response rates are likely to experience greater rates of omissions and undercount.

76. Data shown in Table 2.1 indicate the mean self-response rates for Black and Hispanics plurality census tracts are substantially lower than the mean self-response rate for tracts where Non-Hispanic Whites are the largest population of the tract.¹⁰ The self-response rates for Non-Hispanic White plurality tracts (66.6 percent) is 9.7 percentage points higher than that for Hispanic plurality tracts (56.9 percent), and 13 percentage points higher than Black plurality tracts (53.6 percent). The mean response rate for tracts where Asians are the plurality of the population (67.6 percent) is one percentage point higher than that of tracts where Non-Hispanic Whites are the plurality of the population.

77. Since lower self-response rates are related to higher net undercounts and omissions, as shown in Section 1 of this report, the lower self-response rates in the 2020 Census for Hispanics and Blacks shown in Table 2.1 indicate those groups are on course to have higher net undercount and omissions rates in the 2020 Census. If efforts to improve the accuracy of the 2020 Census are reduced by early termination of the data collection period, it is likely to have a disproportionately negative impact on Hispanics and Blacks who have lower self-participation rates.

¹⁰ Table 2.1 shows data released by the Center for Urban Research at the Graduate Center, City University of New York based on self-response rates through August 20, 2020.

| Table 2.1. Mean 2020 Census Tract-Level Self-Response Rates by the Plurality of the Population by Race and Hispanic Origin | |
|--|---|
| Plurality of the Population in the Tract* | Mean Self-Response Rates for Census Tracts by Plurality of Population by Race and Hispanic Origin (through August 20, 2020) |
| Non-Hispanic White | 66.6 |
| Hispanic | 56.9 |
| Non-Hispanic Black | 53.6 |
| Non-Hispanic Asian | 67.6 |
| Source: Obtained from Steve Romalewski, CUNY | |
| * tract where this population was there largest race or Hispanic Origin group. | |

78. Note that the response data shown in Table 2.1 are for census tracts rather than individual households. Nonetheless, it is reasonable to assume an association between the largest population in a census tract and self-response rates in those tracts. In addition, the pattern seen in 2020 is like that seen in previous censuses.

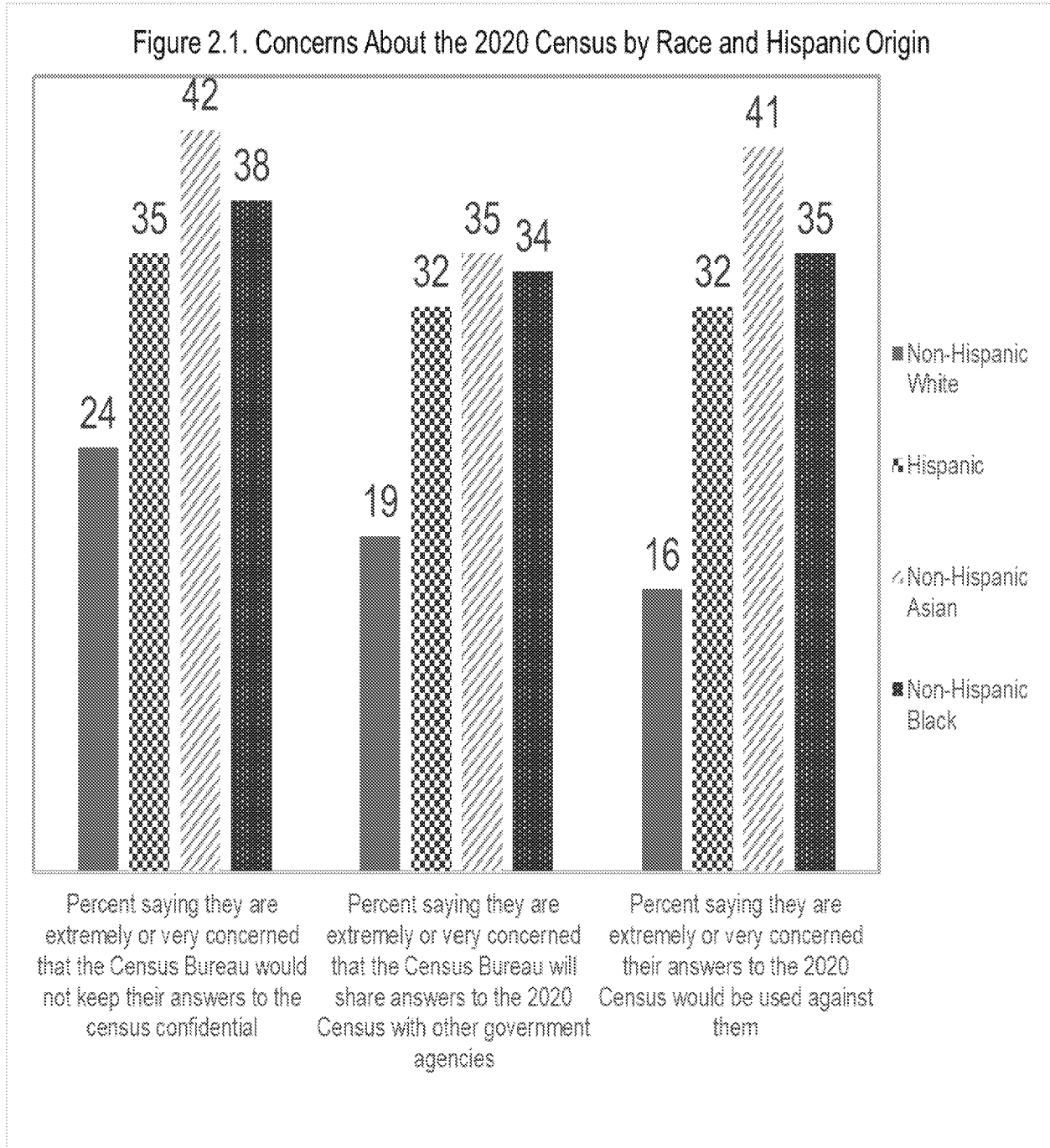
79. While Table 2.1 shows that Asian plurality census tracts have a slightly higher self-response rates than Non-Hispanic White plurality tracts, it is important to recognize that the Asian population is highly diverse and response rates for the overall Asian population are likely to mask big differences among subgroups (U.S. Census Bureau 2012c). One recent report on the Asian population (Lopez, et al. 2017) states, “The U.S. Asian population is diverse. A record 20 million Asian Americans trace their roots to more than 20 countries in East and Southeast Asia and the Indian subcontinent, each with unique histories, cultures, languages and other characteristics.” Some of these differences among Asian subgroups have implications for how the groups interact with census-taking operations (O’Hare 2017 & 2020c: Population Bureau References). Data for the overall Asian population masks important differences for subgroups. For example, poverty is one variable associated with census undercounts and O’Hare (2020c)

shows the young child (age 0 to 9) poverty rates among Asian subgroups vary from a low of 5 percent for Asian Indians to 30 percent in the Hmong population. Consequently, the data for Asians shown in Table 2.1 may not reflect the experiences of many Asian subgroups.

80. One example of this is revealed by noting that Asian plurality tracts in the largest cities of metropolitan areas (over 1 million) have a mean self-response rate (58.8 percent) well below the national response rate (64 percent) and the mean self-response rates for Asian plurality tracts in rural areas (56.9 percent) is well below the national average. On the other hand, Asian plurality tracts in medium-sized cities in metropolitan areas have a mean response rate (71.1 percent) well above the national average. If efforts to improve the accuracy of the 2020 Census are reduced by early termination of the data collection period, it is likely to have a disproportionately negative impact on Asian Americans in the largest cities of metropolitan areas and in rural areas, who have lower self-participation rates. This data is from Center for Urban Research at the Graduate Center, City University of New York.

81. Figure 2.1 shows data from a Census Bureau report (U.S. Census Bureau 2019) indicating the level of concern about the 2020 Census expressed by race and Hispanic Origin groups. Asians, Hispanics, and Blacks express much more concern about the 2020 Census than do Non-Hispanic Whites. These concerns help explain the relatively low self-response rates for

Hispanic and Blacks seen in Table 2.1.



82. The U.S. Census Bureau (2019) Census Barriers and Motivator Survey (CBAMS) survey found 53 percent of respondents thought census data was used “[t]o locate people living in the country without documentation.” And 63 percent thought the Census was used “to help

police and FBI keep track of people who break the law.” Moreover, 28 percent of the CBAMS respondents thought the Census Bureau would not keep answers confidential and 24 percent thought the Census Bureau would share answers with other government agencies. People with this level of distrust in the Census were unlikely to self-respond and resist responding to an enumerator in the NRFU process.

83. With respect to the 2020 Census it is important to note that the foreign-born population and people living in households with foreign-born people are particularly vulnerable to being missed. It is also noteworthy that 34 percent of the people born outside the U.S. are extremely or very concerned that the data they provide in the 2020 Census will be used against them compared to 20 percent of people born in the U.S. (U.S. Census Bureau 2019).

84. Census tracts where the foreign-born population are a disproportionately large share of the total population have lower self-response rates. Data from the Center for Urban Research at the Graduate Center, City University of New York (CUNY) indicates that census tracts where the foreign-born population is more than one-third of the total population had a mean response rate of 59.4 percent on August 20, 2020, compared to a national response rates of 64 percent.¹¹

85. Table 2.2 shows the distribution of the foreign-born population by race and Hispanic Origin. The data in Table 2.2 show that Asians and Hispanics make up the majority (71.4 percent) of the foreign-born population. So, difficulties in getting a complete and accurate

¹¹ The one-third cutoff point for tracts in this analysis was used because it was high enough to make sure the foreign-born was a clearly significant portion of the census tract population but low enough to make sure there were enough tracts meeting the criterion to provide a reliable estimate. Tracts where the foreign-born population was 50 percent or more of the population had even lower mean self-response rates

count of the foreign-born population will affect Hispanics and Asians more than others.

| Table 2.2. Foreign-Born Population in the U.S. by Race and Hispanic Origin: 2018 | |
|---|--|
| | Percent of the Foreign-Born Population in 2018 |
| Non-Hispanic White* | 17.7 |
| Black* | 9.5 |
| Asian* | 27.1 |
| Hispanic | 44.3 |
| Source: U.S. Census Bureau, 2018 American Community Survey Table S0501, retrieved from Data.census.gov on August 4 2020 | |
| * Race Alone, Hispanic may be included in appropriate race categories | |
| Total number of foreign-born people | 44,728,721 |

86. The difficulties in getting complete and accurate count of people in immigrant communities is partly due to a fear of interacting with the federal government. The climate of fear among immigrants has greatly escalated since 2010. Even before there were discussions about adding a citizenship question to the 2020 Census, Census Bureau researchers (Meyer and Goerman 2018; U.S. Census Bureau 2017c and 2017d) found respondents less willing to cooperate given the growing climate of fear and mistrust. After careful review, Meyers and Goerman (2018 Slide 24) conclude, “During multilingual pretesting studies conducted in 2017 and 2018, respondents expressed concerns about participating in the Census Bureau surveys because of fears about their confidentiality.”

87. Based on a series of interactions with interviewees and reports from Census Bureau field staff, the Census Bureau (2017c, page 7) concluded, “Overall, these findings, in various languages from respondents, Field Representatives, and Field Supervisors across the country who have participated in recent projects are raising concerns with CSM regarding potential barriers to respondents participation in the 2020 Census, as well as other Census Bureau surveys.”

88. In a series of focus groups among Latino adults regarding the 2020 Census conducted by National Association of Latino Elected Officials (2018, slide 4), the study, which included a potential citizenship question, concluded, “Hesitation, fear and cynicism arose among focus group participants when they saw a version of the questionnaire.” Data from a recent National Association of Latino Elected Officials survey (2020) indicate nearly half of all Hispanics thought the citizenship question was still on the 2020 Census questionnaire.

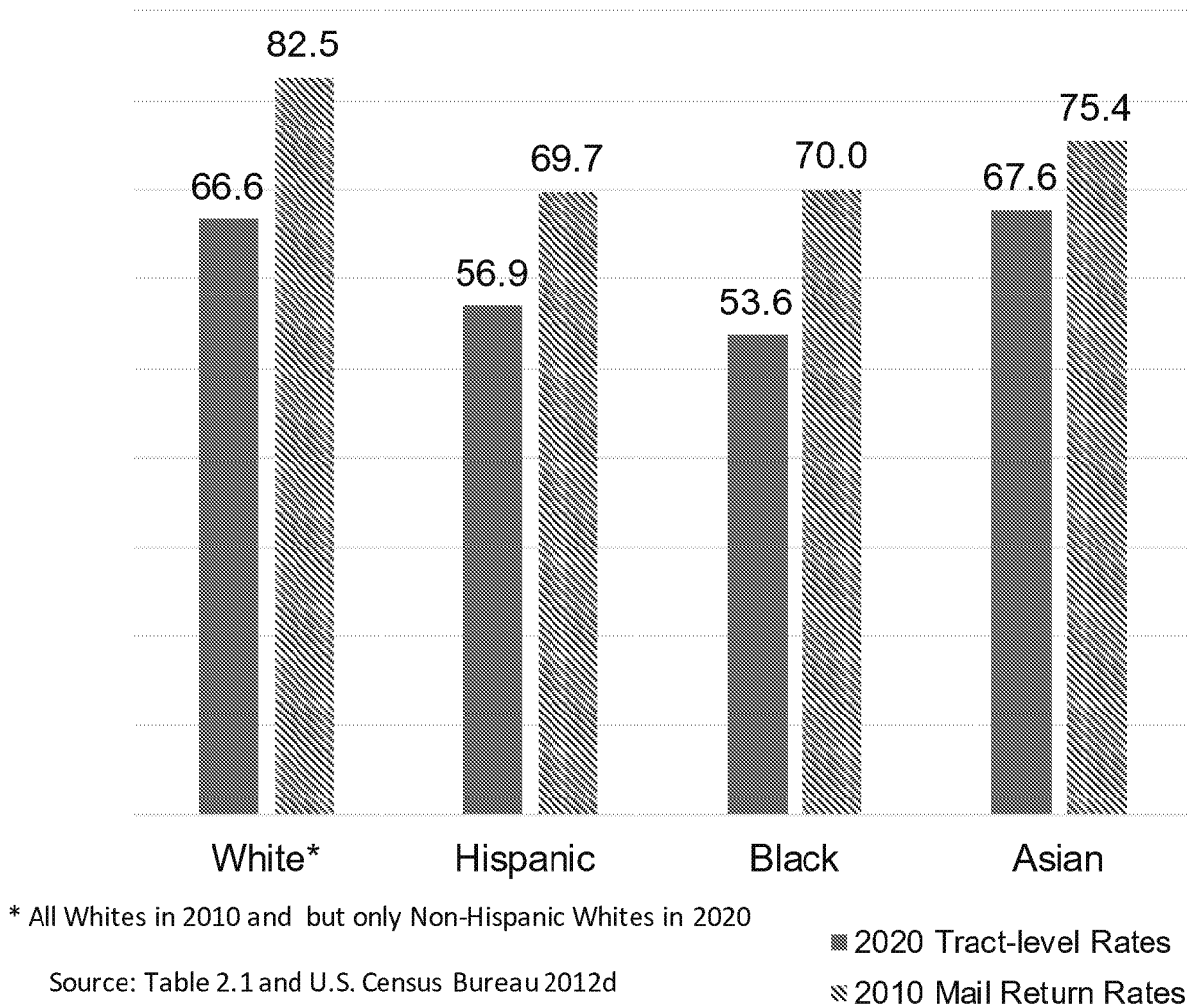
89. In addition to low self-response rates, the difficulty in getting a complete and accurate count of Hispanics and Blacks in the 2020 Census is also reflected in the population composition of census tracts with the lowest self-response rates. Table 2.3 shows the composition of the 20 percent of census tracts with the lowest self-response rates as of August 6, 2020. Hispanics and Blacks are over-represented in these hard-to-count tracts meaning it will be a particularly difficult task to get a complete count of these groups compared to Non-Hispanic Whites.

| Table 2.3. Racial and Hispanic Origin Composition of the 20 Percent of Census Tracts with the Lowest Response Rates Compared to U.S. Population | | |
|---|--|---|
| | Race and Hispanic Origin in the 20% of the Tracts with the lowest self-response rates as of August 6 | Race and Hispanic Origin in U.S. Population |
| Non-Hispanic Whites | 44.1 | 60.2 |
| Hispanics | 25.8 | 18.3 |
| Non-Hispanic Asians | 3.5 | 6.0 |
| Non-Hispanic Black | 22.2 | 12.3 |
| Source: Funders Census Initiative 2020, (August 6 presentation) | | |

90. Figure 2.2 shows the 2020 Census tract-level self-response rates and the 2010 mail return rates by race and Hispanic Origin. Self-response rates and mail return rates are both measures of census participation. Data for 2010 reflect the race of the householder while data for 2020 reflect the plurality of the population in a census tract.

91. Data in Figure 2.2 show that the pattern of participation in the 2020 Census is similar to that in the 2010 Census with respect to race and Hispanic Origin status. In both the 2010 and 2020 Census, the participation rate for Whites is the highest while the rates for Hispanics and Blacks are lower in both years. This underscores the extent to which patterns and relationships seen in past censuses are being repeated thus far in the 2020 Census. It is reasonable to believe the differential response rates seen so far in the 2020 Census are likely to lead to higher net undercounts and omissions for groups with low self-response rates like they have in past censuses. Furthermore, it is reasonable to believe that early truncation of census data collection in the 2020 Census means there will be less time to gather more census responses and the households that are missed, are likely to be disproportionately Hispanic and Black.

Figure 2.2. Self-Response Rates in the 2020 Census and the 2010 Census by Race and Hispanic Origin



92. The data in Tables 2.1, 2.2, and 2.3 focus on demographic groups, but there are also large variations in the self-response rates by geography. Self-response rate variations by state and counties are addressed below.

93. There is a lot of variation in self-response rates across the states. Data released by the Census Bureau (2020c) on August 27, 2020, show 12 states (Alaska, Arkansas, Louisiana, Maine, Mississippi, Montana, New Mexico, Oklahoma, South Carolina, Vermont, West Virginia,

and Wyoming) have self-response rates below 60 percent. On the other hand, there are 4 states (Minnesota, Nebraska, Washington, and Wisconsin) with self-response rates at 70 percent or above. Some of the variation across states is related to the share of their population that is meant to be captured in Update/leave operation rather than the self-response operation. The Update/Leave operation was delayed because of the COVID-19 pandemic.

94. Given the connection between self-response rates and census accuracy based on data from the 1990, 2000 and 2010 Censuses (shown in Section 1) the states with lower self-response rates in 2020 are likely to have higher net undercount and omissions rates. The remaining part of the 2020 Census data collection process is particularly important for states with low self-response rates.

95. For example, Texas is one of the states where self-response rates in the 2020 Census are well below the national average. U.S. Census Bureau (2020e) data from August 27, 2020, shows the self-response rate for Texas is 60 percent compared to 64.6 percent for the nation as a whole. An undercount because of low self-response rates could cost Texas a congressional seat in the re-apportionment process and their fair share of federal funding.

96. New York is another state with below-average self-response rates in the 2020 Census. The 2020 Census self-response rate on August 27, 2020, was 60.7 percent for New York. A high net undercount in the 2020 Census due to low self-response rates in New York could impact the Congressional seats they get in 2020 Census reapportionment, as well as their share of federal funding.

97. It is worth noting that a lower self-response rate and a higher undercount rate in a large state like Texas or New York, will result in a larger number of people missed in the Census

than the same self-response and undercount rates in a small state. In other words, a high net undercount rate in a large state harms more people than the same rate in a small state.

98. In early August, the Census Bureau started the NRFU operation nationwide. But that has not erased differences across the states. Of the fifty states, 12 have enumerated (including self-response and NRFU) less than 75 percent of the population as of August 27, 2020. If the end of the data collection period remains September 30, 2020, this means they must still enumerate more than 25 percent of the households in their state with slightly more than one month remaining. These states captured less than 75 percent of their population in the first 24 weeks of the 2020 Census data collection period but must capture more than 25 percent in about five weeks.

99. It is important to recognize that substate areas vary even more than states in self-response rates. Data retrieved from the Census Bureau (2020e) on August 21, 2020, shows there are 25 counties where the self-response rate is 80 percent or more and 12 counties where the self-response rates is under 20 percent. The connection between self-response rates and census accuracy discussed in Section 1 of this report indicates that variation in self-response rates among geographic areas makes it more likely that some areas will have net undercounts and omissions in the 2020 Census. States rely on census data to draw state legislative districts and census undercounts result in seats shifting away from regions in which people are undercounted. Communities that suffer high net undercounts due to low self-response rates are unlikely to get their fair share of political power in the redistricting process which takes place after every census, and their fair share of federal funding.

100. It is my conclusion that as of August 24, 2020, Census tracts where Hispanics and Blacks are the plurality of the population have lower self-response rates in the 2020 Census than

tracts where Non-Hispanic Whites are the plurality of the population. This indicates Hispanics and Blacks are on a trajectory to have higher net undercounts and omissions rates in the 2020 Census. Ending the 2020 Census data collection period on September 30, 2020, instead of October 31, 2020, means there will be less time available to address data collection improvements for the demographic groups, such as Hispanics and Blacks, with the lowest self-response rates, and will result greater in omissions and undercounts for these demographic groups. If states and groups with low self-response rates had more time for data collection, there would be more time to recover from the racial and Hispanic and state differentials in data collection that we see so far in the data collection process.

3) Reduction in Differentials in 2010 Census and 2020 Census Self-Response Over the Census Data Collection Period

101. Data from the 2010 Census show Hispanic, Asians, and Blacks were a larger share of the population responding later in the data collection period than those responding in the earlier portion of the data collection period. Consequently, changes to the end of the data collection period impact Hispanics, Asians, and Blacks more than Non-Hispanic Whites.

102. A U.S. Census Bureau (2012d) report provides mail return rates for a date around the middle of the 2010 Census self-response period (April 19, 2010) and at the end of the self-response period (September 7, 2010) by race and Hispanic Origin status. The April 19, 2010 date was used by the Census Bureau because that is when the Census Bureau determined which housing units they would follow up with a visit from a census enumerator. They call this the NRFU universe. The September 7, 2010 date reflects all self-responses in the 2010 Census.

103. The indicator of census participation used in Table 3.1 is the mail return rate. According to the Census Bureau (2012d, page vi) “Mail Return Rates reflect the percentage of

occupied housing unit that returned their questionnaire in time to avoid enumeration in Nonresponse Followup.”

104. Data in Table 3.1 show that between April 19, 2010 and the end of the data collection on September 7, 2010 the mail return rates for Whites increased by 3.2 percent points compared to 4.6 percent for the Black population, 4.5 percentage points for the Hispanic population, and 4.4 percent for the Asian population. In other words, Blacks, Hispanics, and Asians were responding at a higher rate than Whites during the latter part of the data collection period (April 19, 2010 to September 7, 2010). Hispanics, Asians, and Blacks were a disproportionately high share of those responding between April 19, 2010 and the end of data collection period than they were between the start of data collection and April 19, 2010. Given the higher response rates of Hispanics, Asians, and Blacks near the end of the data collection process, changes in the collection process near the end of the data collection process are more likely to impact those groups.

| Table 3.1 Percentage Point Difference Between the Middle and the End of Self-Response Phase of the 2010 Census by Race and Hispanic Origin | | | | |
|--|----------------------|-------------------------|--|--|
| | Mail Return Rates* | | | |
| | as of April 19, 2010 | as of September 7, 2010 | | Percentage Point Changes from April 19 to September 7 2010 |
| White* Alone | 79.3 | 82.5 | | 3.2 |
| Black Alone | 65.4 | 70.0 | | 4.6 |
| Asian Alone | 71.0 | 75.4 | | 4.4 |
| Hispanic | 65.2 | 69.7 | | 4.5 |
| * Source;; U.S. Census Bureau (2012). "2010 Census Mail Response Rate/Return Rates Assessment Report," 2010 CENSUS PLANNING MEMORANDUM SERIES, No. 198, U.S. Census Bureau, Washington DC. | | | | |
| * Data for Non-Hispanic Whites not available | | | | |

105. There is another way of looking at this data that leads to the same conclusion. Table 3.2 shows the percentage point gap between the mail return rates of Whites and minorities

(Hispanic, Asians and Blacks) around the middle of the 2010 Census data collection period (April 19, 2010) and at the end of that period (September 7, 2010). For Hispanics, Asians and Blacks, the gaps between their self-response rates and those of Whites are smaller at the end of the data collection period than it was at the middle of the data collection period. This suggests that the longer the data collection period lasts, the smaller the gap between self-response rates of minorities and Whites.

| Table 3.2 Percentage Point Difference Between Middle and End of Self-Response Phase of the 2010 Census by Race* and Hispanic Origin of the Householder | | | | | |
|--|----------------------|-------------------------|--|--|-------------------------|
| | Mail Return Rates | | | Percentage Point Difference Between White and Minorities April 19, and September 7, 2010 (Minority-White) | |
| | as of April 19, 2010 | as of September 7, 2010 | | as of April 19, 2010 | as of September 7, 2010 |
| White Alone* | 79.3 | 82.5 | | | |
| Black Alone | 65.4 | 70.0 | | -13.9 | -12.5 |
| Asian Alone | 71.0 | 75.4 | | -8.3 | -7.1 |
| Hispanic | 65.2 | 69.7 | | -14.1 | -12.8 |
| Source: U.S. Census Bureau (2012). " 2010 Census Mail Response Rate/Return Rates Assessment Report," 2010 CENSUS PLANNING MEMORANDUM SERIES, No. 198, U.S. Census Bureau, Washington DC. | | | | | |
| * Data for Non-Hispanic White not available | | | | | |

106. The Census Bureau data for 2010 Census mail return rates are not available for Non-Hispanic Whites, only for Whites. This is important because some Hispanics are counted in the White race category but are not included in the Non-Hispanic White category. Since Hispanics have lower self-response rates than Whites, including some Hispanics in the White category depresses the White rate and leads to false comparison between minorities and the majority population. Since the data for “Whites” include data for some Hispanics these figures do not reflect the real difference between minorities and Non-Hispanic Whites. The difference

between Whites and minorities shown in Table 3.1 and 3.2 would undoubtedly be larger if we had data for Non-Hispanic Whites.

107. Data from the 2020 Census show a similar pattern to the 2010 Census with respect to a larger share of the population responding later in the data collection period being Hispanic, Asian, and Black. Table 3.3 shows the mean response rates on April 30, 2020, and August 20, 2020, for tracts by the race and Hispanic Origin plurality of the population in the tract. From April 30, 2020, to August 20, 2020, the percentage point increase in the mean response rates for Hispanic plurality tracts, Asian plurality tracts, and Black plurality tracts was larger than for Non-Hispanic White plurality tracts. The increase was 7.4 percentage points for tracts where Non-Hispanic Whites were the plurality of the tract, compared to 9.6 percentage points for Hispanic plurality tracts, 10.3 percentage points for Asian plurality tracts, and 8.3 percent for Black plurality tracts.

| Table 3.3. 2020 Census Self-Response Rates by Race and Hispanic Origin Plurality of Tracts by Date | | | |
|---|----------------------|-----------------------|--|
| | Self-Response Rates | | Percentage Point Change May 1, 2020 to August 20, 2020 |
| | as of April 30, 2020 | as of August 20, 2020 | |
| Plurality of Population In Tract | | | |
| Non-Hispanic White* | 59.2 | 66.6 | 7.4 |
| Hispanic | 47.3 | 56.9 | 9.6 |
| Non-Hispanic Asian* | 57.3 | 67.6 | 10.3 |
| Non-Hispanic Black* | 45.3 | 53.6 | 8.3 |
| Source: Data from April 30, 2020 Funders Census Initiative 2020 and data for August 20, 2020 obtained from Steve Romalewski at CUNY | | | |
| *Race Alone or in Combination | | | |

108. Table 3.4 shows differences between Whites and minorities (Hispanic, Asians and Blacks) in terms of 2010 Census mail return rates, net undercount rates, and omission rates. The