



RESEARCH REPORT

Simulating the 2020 Census

Miscounts and the Fairness of Outcomes

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Executive Summary

Population censuses have never been and never will be perfect. The 2020 Census was not likely perfect, either. The challenges and obstacles to conducting the 2020 Census were numerous and varied—from its politicization to the pandemic—and accuracy and fairness were likely affected.

Questions and concerns have been raised about the quality of the 2020 Census and whether the data will be as accurate as previous censuses (GAO 2020c; Thompson 2021). The goal of the Urban Institute’s study was to address such questions about quality and provide additional data about the 2020 Census’s accuracy and fairness. Urban created an innovative methodology—a simulation of the 2020 Census—to better understand the decennial census’s performance.

Exploring the 2020 Census’s Accuracy and Utility

To offer additional insights on the 2020 Census’s accuracy and utility, the Urban Institute constructed a person-level microsimulation model to explore these questions. A microsimulation model allows us to simulate different plausible scenarios for miscounts and fairness in the 2020 Census to understand how factors may influence its accuracy and corresponding implications for political representation and allocation of federal resources.

In this case, our “what if” scenarios explore what both a simulated 2020 Census count and a hypothetical full count could look like for the United States by geography and demographics, as well as scenarios for apportionment and Medicaid funding.

This novel approach creates plausible 2020 Census counts and then tests them under various evidence-based conditions. As the findings in this report demonstrate, these data serve as an additional check on the quality of the census count and further elucidate the real implications of an imperfect 2020 Census for the nation over the next decade. Specifically, we show the following:

- The 2020 Census likely had a net undercount—disproportionately larger for specific groups and places—which suggests less accuracy than in the 2010 Census.
- Such undercounts have implications for the fair allocation of funding and congressional representation across the states.
- Urban’s microsimulation model illustrates how a hypothetical full count would produce fairer results.

What Factors Contribute to the Final Count’s Accuracy and Fairness?

The past decade was marked by internal and external factors that have implications for the count. They include demographic change in the US, the political climate, the COVID-19 pandemic, natural disasters, and the resulting operational changes made to the 2020 Census to account for changing times and realities.

Events and decisions in the decade leading up to 2020 Census Day may have had more impact on the final counts than in previous decades. Traditionally hard-to-count groups increased as a share of the population. Precensus funding shortfalls at key times limited the testing of new census procedures, and late disputes over census content exacerbated uncertainty. Then the pandemic affected living arrangements, complicated in-person follow-up counts, and delayed postenumeration data cleaning and other processes.

This report describes the events leading up to Census Day, the prolonged period of fieldwork and data processing because of the pandemic, and how these factors contribute to the final count’s accuracy and fairness. The challenging environment in which the 2020 Census was conducted suggests the need for additional benchmarks—such as Urban’s microsimulation model—to assess the 2020 Census’s quality, accuracy, and fairness.

Estimating Census Counts, Testing Scenarios, and Exploring Outcomes

Urban created the unique data presented in this report for this project as an important benchmark to assess the quality of the 2020 Census. They were created in a two-step process. First, we projected the US population as of April 1, 2020, or Census Day. Second, we adjusted our projected population with known factors likely to affect the census and tested two scenarios: a **simulated 2020 Census** and **hypothetical full count**. We then explored potential outcomes, such as apportionment and the allocation of federal Medicaid funding.

This study is based on the best data available and is grounded in robust projections and microsimulation methodologies. However, as is true with any data and analyses, limitations exist and we urge caution in interpreting the findings.

The undercount was likely not as severe as expected, but who was undercounted and overcounted varies. Our simulation of the 2020 Census finds the following:

1. **There likely was an overall 0.5 percent net undercount of the US population.** Although different from the 2010 count, which had nearly perfect net accuracy, it was perhaps not as severe an undercount as some have feared.
2. **Considerable variation exists in who was undercounted and overcounted overall in the 2020 Census.** Net accuracy is important, but fairness also matters.
 - » We find that the true total populations of Mississippi and Texas were undercounted in our simulated 2020 Census by 1.3 and 1.28 percent, respectively, while Minnesota’s population was net overcounted by 0.76 percent. Such differences matter for these states for the next decade—Mississippi and Texas residents will receive less of their fair share of federal funding for infrastructure, health care, and children’s programs. In contrast, Minnesota residents will receive more.
 - » For example, we find in our simulations that if the residents had been counted accurately in the 2020 Census, Texas would receive over \$247 million more and Minnesota would receive \$156 million less in 2021 federal Medicaid reimbursements. A fair and accurate census impacts people’s well-being, and these outcomes can be disparate across the nation.
3. **Those hardest to count in recent decennial censuses were again likely undercounted in the 2020 Census.** For each hardest-to-count group, equity issues arise with the count’s fairness, how resources will be distributed, and who will miss out on their fair share of political representation and funding:
 - » Black and Hispanic/Latinx people had a net undercount of more than 2.45 and 2.17 percent, respectively, in our simulated 2020 Census.
 - » Young children, or those younger than age 5, were likely to be net undercounted by 4.86 percent.
 - » Nationwide, renters were likely to be undercounted by 2.13 percent overall.
 - » Households with a noncitizen present were likely undercounted by 3.36 percent overall.

Counting the nation’s population fully is becoming increasingly complicated. Innovations are needed to better understand the quality of the census, its fairness, and its implications for the following decade.

It is impossible to change the outcomes of the 2020 Census, but with adequate planning and innovation, the 2030 Census can be improved for the hardest-to-count groups and places. These efforts require us to collectively recognize how critical it is to invest in the decennial census and value it as a core component of our democracy.

Simulating the 2020 Census

Population censuses—including decennial censuses conducted in the US—have never been and never will be perfect. Recent history points to examples of imperfections in enumerating the country. The 1990 Census had such notable flaws in miscounts by race that a statistical adjustment to boost accuracy was attempted and then rejected by the US Supreme Court.¹ In 2010, the census was touted as highly accurate because its count came within a fraction of a percentage point of an independently generated survey-based estimate. Yet this was the propitious result of counterbalancing about 10 million people who were erroneously included with about 10 million people who were omitted overall.² Further, accuracy in 2010 came at the expense of fairness; those who were overcounted were more often white, while those undercounted were more often people of color.

The 2020 Census was not likely perfect either. The challenges and obstacles to conducting the 2020 Census were numerous and varied—from its politicization to the pandemic—and its accuracy and fairness were likely affected. Our previous research offered a sense of the magnitude of possible miscounts in the 2020 Census under milder challenges than what unfolded (Elliott et al. 2019). In that research, we showed that historically undercounted groups, including Black, Hispanic/Latinx, and young children were at greater risk of not being enumerated in 2020 than their counterparts.

Because no census has ever been perfectly accurate, the issue is not *whether* accuracy was achieved, but its *utility* for specific purposes such as apportionment and allocation of federal resources. At present, many researchers are investigating the data quality of the 2020 Census to better understand its accuracy and its subsequent utility. Since April 2021, the US Census Bureau has released various operational measures that indicate the quality of the data collection efforts,³ and outside researchers, including an American Statistical Association task force, independently reviewed these quality metrics (ASA 2021). Even with such scrutiny, the magnitude of inaccuracies in the 2020 Census can never be known with certainty and will undoubtedly vary by geography and subpopulations. The need for additional research on this topic is considerable.

To offer additional insights on the 2020 Census's accuracy and utility, Urban constructed a person-level microsimulation model to explore these questions. A microsimulation model allows us to simulate different plausible scenarios for miscounts and fairness in the 2020 Census to understand how factors may influence its accuracy and corresponding implications for political representation and allocation of federal resources.⁴ In contrast to others' work analyzing data quality, this is a novel approach that creates plausible 2020 Census counts and then tests them under various evidence-based conditions. As the findings in this report demonstrate, these data serve as an additional check on the quality of the

census count and further elucidate the real implications of an imperfect 2020 Census for the nation over the next decade. Specifically, we show the following:

- The 2020 Census likely had a net undercount—disproportionately larger for certain groups and places—which suggests less accuracy than in the 2010 Census.
- Such undercounts have implications for the fair allocation of funding and congressional representation across the states.
- Urban’s microsimulation model illustrates how a hypothetical full count would produce fairer results.

BOX 1

Glossary

Throughout this report, we use technical terms—some also used by the US Census Bureau—which we describe below.

- **Administrative records.** These are data sources, typically pulled from other federal sources, that will be used to supplement address and resident information on the 2020 Census when there are information gaps or when households do not respond.
- **Enumeration.** This is the count of people, households, firms, or other important items in a geographic level at a particular time.
- **Erroneous enumerations (or overcounts).** These are people or housing units who were counted but should not have been enumerated. This includes counting the same person at two different locations, a household counting a person who died before or was born after Census Day, or the inclusion of vacant or short-term housing units (such as vacation rentals).
- **Federal Medical Assistance Percentage (FMAP).** This is the federal funding formula used to determine the percentage of each state’s expenditures on medical programs that will be reimbursed by the federal government. It is a ratio of per capita state income to per capita total US income, which both depend on census counts.
- **Imputation.** This is the process of assigning data, through statistical procedures, when they are missing. This is one of the last data-processing steps before the census is finalized.
- **Internet self-response (ISR).** This option was available on the 2020 Census for residents to answer questions online. The Census Bureau prioritized the “Internet First” mode in the 2020 Census, encouraging responses to be submitted online rather than by phone or paper form.
- **Microsimulation model.** This is a computer program that mimics the operation of government programs and demographic processes on individual (i.e., people and households) members of a

population to estimate how demographic, behavioral, and/or policy changes might affect these members and better understand the effects of current programs.

- **Nonresponse follow-up (NRFU).** This is the period during decennial census operations when field staff, like enumerators, are sent to nonresponsive residences to conduct the count in-person.
- **Omissions (or undercounts).** These are people and households that should have been counted but for various reasons were missed in the final census count.
- **Post enumeration survey (PES).** This survey is part of the Census Coverage Measurement (CCM) program conducted after the 2010 Census to understand how successful the census was in counting the American public.

Urban's data and analytic scenarios used in the report are as follows:

- **Initial projections.** Urban created projected data for the entire US population on April 1, 2020, based on US Census Bureau data.
- **Simulated 2020 Census.** This scenario is Urban's simulation of the 2020 Census that accounts for known measurement limitations that could promote miscounts and applies adjustments for such factors to Urban's initial projections.
- **Hypothetical full count.** This scenario takes our simulated 2020 Census and eliminates omissions and removes any erroneous enumerations. It assumes no missing or duplicated people in the 2020 Census count.
- **Official 2020 Census counts.** We refer to published resident population and apportionment census counts for the nation and states that were released on April 26, 2021, from the Census Bureau compared with Urban's data.

The State of the 2020 Census

Censuses are not conducted in perfect worlds; perfect censuses are impossible. Questions of accuracy and fairness always emerge with the release of final counts, and the 2020 Census was no exception. Court cases were launched in *advance* of the first release of 2020 Census numbers challenging its accuracy.⁵ What matters, however, is not that a perfectly executed census occurred, but that the magnitude of likely errors is tolerable and that resulting counts have utility for their intended purposes.

Events that occurred and decisions that were made in the decade leading up to Census Day on April 1, 2020, may have had more impact on the final counts than in previous decades. Traditionally hard-to-count groups increased as a share of the population. Precensus funding shortfalls at key times limited

the testing of new census procedures, and uncertainty was exacerbated by late disputes over census content. Then the pandemic affected living arrangements, complicated in-person follow-up counts, and delayed postenumeration data cleaning and other processes.

In this section, we describe the events leading up to Census Day, the prolonged period of fieldwork and data processing because of the pandemic, and how these factors contribute to the accuracy and fairness of the final counts. The challenging environment in which the 2020 Census was conducted suggests the need for additional benchmarks—such as Urban’s microsimulation model—to assess the 2020 Census’s quality, accuracy, and fairness.

Factors Affecting the 2020 Census Count

The past decade was marked by several factors—both external to the census and driven by operational changes within it—that have implications for the count’s completeness and fairness. They include demographic change in the US, the political climate, the COVID-19 pandemic, natural disasters, and the resulting operational changes made to the 2020 Census to account for changing times and realities.

DEMOGRAPHIC CHANGE

Since the 2010 Census, the United States has changed in ways that affect the overall accuracy and fairness of the census counts. Data from the intervening decade suggest that there have been shifts in the population that likely affected self-response and data quality in the 2020 Census; this is especially important given what we know about those who have historically been the hardest to count (GAO 2018). Demographic changes such as an aging population, greater racial/ethnic diversity, shifts in noncitizens, and lower rates of homeownership could contribute to differences in the count regardless of other factors. We document demographic changes here and why they were factored into the 2020 Census projection data developed for this study.

Since 2010, the average age of the US population has increased.⁶ Historically, those ages 50 and older have had higher percentages of overcounts in the census and those younger than age 5 have been historically undercounted (Fernandez, Shattuck, and Noon 2018; O’Hare 2015). On balance, a shift to an older population in the US in 2020 would have produced a *smaller* net undercount for the overall US population but not necessarily a fairer count if children continued to be missed at higher rates.

Between 2010 and 2020, the US also became more racially and ethnically diverse.⁷ This has implications for the 2020 Census because historically households with a non-Hispanic/Latinx white head of household have had higher percentages of overcounts and lower percentages of being missed

by the census, compared with Hispanic/Latinx, non-Hispanic/Latinx Black, Asian and Pacific Islander, and American Indian and Alaska Native households (Elliott et al. 2019). For these reasons, we expect greater racial/ethnic diversity likely contributed to a larger net undercount for the overall US population.

Finally, homeownership decreased slightly from 2010 to 2020.⁸ Census researchers have found that economically advantaged homeowners have the highest self-response rates, including by the internet (Baumgardner, Griffin, and Raglin 2014). Further, renters are often noted as among the hardest to count (GAO 2018). So a shift away from homeownership could have contributed to a larger net undercount in the 2020 Census.

POLITICIZATION OF THE CENSUS

Political discourse about immigration, including attempts to add a citizenship question, may have affected people's willingness to participate in the 2020 Census. As early as September 2017, researchers within the US Census Bureau found increased reluctance to participate in research activities amid anti-immigration policies and rhetoric.⁹ This included the Muslim Ban, dissolution of the DACA (Deferred Action for Childhood Arrival) program, and actions of ICE (Immigrant and Customs Enforcement).¹⁰ This rhetoric contributed to unprecedented confidentiality concerns, particularly among immigrants and people of color (Meyers 2017). Further, a 2020 Census study found that nearly half of the study's participants expressed some level of concern about the confidentiality of their responses (McGeeney 2019).

Controversy over the last-minute addition of the citizenship question could have also heightened growing fears and suppressed household participation. The untested question gained national media attention, raising concerns of a potential chilling effect among some groups, including Hispanic/Latinx people and immigrants (Baum et al. 2019; Kissam et al. 2019).¹¹ In July 2019, a divided Supreme Court ruled that the Commerce Department's decision to include this question violated federal law.¹² Even with the question's exclusion, the administration planned to use administrative records to try to determine the US citizenship status of every adult at the block level (Deaver 2020, 6). For these reasons, many experts assume that some households likely did not participate and noncitizens were missing from household rosters, even when households responded, because of fear and government distrust. This suggests possible further reduction of the 2020 count's accuracy.

COVID-19

As part of operational and budget planning, the Census Bureau factors in the possibility of a natural disaster affecting its decennial data collection. In 2017, its cost estimate included a cushion of 10 percent additional funding in case of “unknown unknowns” that might emerge during fieldwork (Goldenkoff and Powner 2018, 26). However, 2020 proved to be an extraordinary year, with natural disasters like hurricanes, wildfires, and most notably, the COVID-19 pandemic.

The US government declared a pandemic on March 13, 2020,¹³ a day after the 2020 Census began mailing information to households to participate (GAO 2020a). This timing likely affected census participation in multiple ways. For those who were homebound and most likely to self-respond, having a web-based option likely enhanced participation; nearly two-thirds of US households self-responded to the census and primarily online.¹⁴ For those who are hardest to count, however, field operations and staff hiring were delayed by the pandemic, in-person community-based outreach was halted, and public health concerns about the safety of conducting in-person follow-up to nonresponsive households were heightened (GAO 2020b). Indications exist that enumerating apartment dwellers became harder in 2020, in part because of the pandemic, further contributing to concerns about coverage.¹⁵

Such delays and postponements have prompted concerns about equity in the census. Communities hardest hit by COVID-19 early in the pandemic tended to be those inhabited by the hardest to count, including areas with lower incomes and Black and Hispanic/Latinx communities.¹⁶ Further, many households and those living in dormitories and college towns relocated at the start of the pandemic, raising concerns about how people would answer the census based on their usual residence during COVID-19.¹⁷ In addition to delayed fieldwork, the schedules for data-processing activities and data releases, such as the official apportionment counts and redistricting data released to the states, were also extended.¹⁸ Overall, the full scope of the pandemic’s effects on the 2020 census, and particularly on the hardest-to-count communities, will be better understood when additional quality metrics are released from the Census Bureau and analyzed in depth (GAO 2020a).

OPERATIONAL CHANGES

Every decennial census adjusts its operational procedures to reflect technological advancements, the changing patterns of society, or funding limitations. For the 2020 Census, the most significant technological advancement was the introduction of a web-based option, or the Internet Self-Response (ISR), for households to complete the count (Decennial Census Management Division 2018). This change reflects the growing reach of technology, as well as the need to save on costs (US Census Bureau 2018). Although the Census Bureau had been using web-based approaches in other data-collection

efforts—notably the American Community Survey—2020 was the first time it was not only available on the census, but also actively encouraged as an option (US Census Bureau 2018).

Overall, the ISR was a successful operational change with 53.5 percent of US households answering via the Internet, contributing to a total US self-response rate of 67 percent,¹⁹ surpassing what was projected in official operational plans (US Census Bureau 2018). Higher self-response on the census is generally associated with better quality data. A looming question, however, is whether duplications increased because of ISR; households could respond via the Internet whether they provided their household's Census ID or not (Decennial Census Management Division 2018). Although other identifiers can be used to deduplicate records if no Census ID is provided,²⁰ it is likely that some duplications persisted and contributed to a net overcount. Until additional data are released by the Census Bureau about the ISR's performance we will not know how it contributed to error.

Another advancement in the 2020 Census was the expanded use of administrative records—using other government or private entity data—to verify addresses, improve nonresponse follow-up by enumerators working in the field, and provide proxy data when households did not complete the census (Deaver 2020). Originally, the Census Bureau intended to use administrative records in the 2020 Census only if multiple data sources substantiated the household and its residents (Deaver 2020). Toward the end of the fieldwork period, which was curtailed by the pandemic and hurricanes, the Census Bureau began using administrative records data for nonresponse households, even if only a single source of such data were available because of perceived higher quality relative to alternatives like imputation.²¹ Overall, 5.6 percent of all households were enumerated with administrative records nationwide, but it remains unclear whether these data improved 2020 Census performance.²²

Finally, to trim funding, better leverage field staff, and create a more efficient nonresponse follow-up period, the 2020 Census introduced an innovative adaptive design that used technology and paradata to assign work to enumerators in real time as cases opened and closed (Decennial Census Management Division 2018). The approach was developed, tested, and researched throughout the preceding decade to develop the dynamic approach applied in the 2020 Census (Konicki and Adams 2015). Based on developmental research, adaptive design likely improved data collection and reduced errors.

As discussed, the COVID-19 pandemic created major operational adjustments, including delays in the fieldwork and data-processing periods, a shortened field operations schedule, and changes in protocols to accommodate new schedules. Funding shortfalls in the decade leading up to the 2020 Census also increased risks to its successful implementation (Goldenkoff and Powner 2018). Innovations, whether planned or implemented mid-census, may have improved the quality of the final

2020 Census data, but we will not have such insights until findings from the 2020 PES are released in the coming year (GAO 2020a).

ACCOUNTING FOR FACTORS IN URBAN'S SIMULATED 2020 CENSUS

Overall, factors that may have influenced the 2020 Census—from real demographic change in the past decade to operational changes to external factors like COVID-19 and political forces—have created a situation with many unknowns. The data quality and outcomes of the 2020 Census could be less predictable than in previous decades. Although self-response rates were higher than anticipated, early evidence suggests that differential self-response rates by age and race could generate unfairness in the final counts (O'Hare and Lee 2021; Santos 2020). Although groups external to the US Census Bureau, including an American Statistical Association sponsored research panel, are investigating the quality of the 2020 Census, such research relies on the Census Bureau's own data quality indicators.²³

Benchmarks external to the US Census Bureau that explore the quality of the 2020 Census are needed. Urban's microsimulation model is an effort to create external, yet plausible benchmarks grounded in census data and derived independently. Accordingly, our simulated 2020 Census controls for factors such as demographic shifts over the past decade and self-response rates to the 2020 Census and adjusts for estimates of how households with noncitizens may respond to the census. Our simulated 2020 Census cannot control for factors that are harder to measure, such as pandemic-related obstacles, elevated distrust in government, and late operational changes such as increased use of administrative records. Nevertheless, Urban's microsimulation data presents an innovative way to independently evaluate the census by simulating it and creating alternative scenarios that help us better understand the bounds of data quality and implications for our nation's population from our once-a-decade count.

Methodology

The unique data presented in this report were created for this project as an additional benchmark to assess the quality of the 2020 Census. They were created in a two-step process. First, we projected the US population as of April 1, 2020, or Census Day, to estimate census counts overall and by demographic groups and geography. Second, we used the projected census counts to adjust the population in different ways to test scenarios and explore potential outcomes, such as apportionment and allocation of federal Medicaid funding.

Projecting the US Population

As a basis for our microsimulation model, we began with a single projection of the actual population on April 1, 2020, or Census Day. In this section, we briefly describe our method for projecting the populations of US states at census time, with specific details available in the appendix.

We started with estimates of 2015–19 combined American Community Survey (ACS) data from the US Census Bureau with a total of 15,947,000 person-level cases. For every US state, we projected the population by racial/ethnic groups, specifically non-Hispanic/Latinx white, Black, American Indian and Alaska Native, Asian, Hawaiian and Pacific Islander, and Hispanic/Latinx of any race. Then, within each racial/ethnic group in a state, we projected the population by age group. We then projected the population living in households owned or mortgaged versus rented and finally projected the population by household citizenship status.²⁴ These population estimates provide the foundation for projecting 2020 miscounts.

We estimated the Census Day population by adjusting person-level analytic weights. We used Demographic Analysis (DA) Population Estimates (Jensen et al. 2020), with populations by single years of age, to calibrate and mature the US population weights from that provided in the 2015–19 ACS dataset to the US Census Bureau estimates for April 1, 2020. We made separate adjustments at the state level so the population estimates were consistent with the actual 2020 Census apportionment counts by state.

How the Microsimulation Model Works

In the social sciences, a microsimulation model is a computer program that mimics the operation of government programs and demographic processes on individual (“micro”) members of a population, such as people, households, or businesses. For each observation in a large-scale, population-based survey dataset, the computer program simulates outcomes of interest—such as how likely someone will be undercounted or overcounted in the 2020 Census—by applying actual or hypothetical program rules to the survey data about that observation. Each individual result is multiplied by whatever “weight” is associated with the unit in the survey data that contributes to a population projection according to the person’s demographic characteristics. The weighted individual results are added together to obtain aggregate results, which, in this study, reflect the entire population of the US.

Microsimulation models require substantial time to develop and maintain but allow analyses usually not supported by other models. Microsimulation models capture interactions between multiple programs or policies, tabulate results by a wide variety of socioeconomic characteristics, and allow

almost unlimited “what if” testing of prospective government policies. In this case, our “what if” scenarios explore what both a simulated 2020 Census count and a hypothetical full count could look like for the US by geography and demographics, as well as scenarios for apportionment and Medicaid funding. See the appendix for additional methodological details about the microsimulation model’s construction.

BOX 2

Urban’s Microsimulation Scenarios

Urban’s findings are derived from scenarios tested with our microsimulation model. These scenarios start with Urban’s projected population data, calibrated to April 1, 2020, as their foundation.

- First, we explore a “**simulated 2020 Census**” scenario to determine what the final 2020 Census count—including miscounts—is most likely to be for the US population. We make a series of adjustments to our projected US population based on factors known to influence the count’s accuracy, including housing tenure, age, race and ethnicity, the presence of a noncitizen in a household, and self-response rates to the 2020 Census. Thus, we simulate the likely 2020 Census environment and its limitations to achieving a complete count. This scenario answers the question, “What will the final 2020 Census count be if we replicate known factors that will produce miscounts?” In this scenario, we find that nationally, the 2020 Census likely produced an average overcount of 3.6 percent and an average undercount of 4.1 percent, yielding a total net undercount of the US population of 0.5 percent.
- Second, we explore a “**hypothetical full-count**” scenario where we assume that there are no overcounts or undercounts among anyone in the US population. For this scenario, we nullify effects of net overcounts and net undercounts for all people. This scenario answers the question, “What if the true resident population of the US were counted completely, accurately, and only once?” Through this scenario, we explore the outcomes that a fair and accurate count would produce.

Findings

In this section, we present data for these scenarios for all states and the 20 largest metropolitan areas, key demographic groups, and outcomes such as apportionment and Medicaid reimbursements by state.

Assessments of 2020 Census Performance for States and Large Metropolitan Areas

URBAN'S ASSESSMENT OF NATIONAL AND STATE MISCOUNTS IN THE 2020 CENSUS

According to the official 2020 Census counts released on April 26, 2021, the US population had 331,449,281 residents living in the 50 states and Puerto Rico on April 1, 2020.²⁵ Urban produced a **simulated 2020 Census** to understand how the 2020 Census likely performed when enumerating the total resident population as of April 1, 2020. In this simulated 2020 Census, we account for shifting demographics, past decennial census performance, operational changes, and self-response rates to the 2020 Census. In Urban's model, we find that the 2020 Census likely had 4.1 percent omissions (undercounts) and 3.6 percent erroneous inclusions (overcounts), culminating in an overall net undercount of 0.5 percent (table 1).

For comparison, the US Census Bureau's PES found that the 2010 Census had 3.3 percent omissions (i.e., undercounts not captured by imputation) counterbalanced by about 3.3 percent overcounts, which produced a net undercount close to zero.²⁶ We will not know the official accuracy assessment of the 2020 Census until the US Census Bureau releases its PES results in late 2021 or early 2022.

If the 2020 Census were a full count—if all people were enumerated—we would have different outcomes. In Urban's **hypothetical full-count scenario**, we assume that being overcounted or undercounted would not vary by demographic and other factors, as they do in Urban's simulated 2020 Census, and it would be a fairer count. In other words, with our hypothetical full-count scenario, we show what the true resident population is and assume everyone was counted once. In our hypothetical full-count scenario, the US resident population is 333,132,506. This suggests that the US failed to count 1,683,225 people in 2020, with a net undercount of 0.51 percent (table 1).

In Urban's simulated 2020 Census, some states had higher percentages of miscounts than others. For example, Alaska, Georgia, Louisiana, Mississippi, New Mexico, New York, and Texas all had likely undercounts that were greater than 1 percent of their population. Excluding the District of Columbia, the highest net undercounts for states in Urban's simulated 2020 Census were in Mississippi and Texas, where 1.3 and 1.28 percent, respectively, of each state's "true" total population was undercounted in

our model. Because Texas has such a large population, this means that 377,187 residents in the true population of Texas were not counted in the 2020 Census. Framed in different terms, this means that more than one-fifth of all people not counted in the 2020 Census resided in Texas. A combination of factors—including demographic diversity and lower self-response rates—contributed to undercounts in these states. In Urban’s model, Texas had the largest undercount among the 50 states at 5.16 percent, which is consistent with historical patterns (Elliott et al. 2019).

In contrast, four states—Iowa, Minnesota, New Hampshire, and Wisconsin—all had overcounts of 0.5 percent or more in Urban’s simulated 2020 Census. Minnesota had the highest net overcount in Urban’s simulated 2020 Census, where 0.76 percent of its population was overcounted overall. This is not surprising; Minnesota had the highest self-response rate with 75.1 percent of its population having completed the 2020 Census on their own.²⁷ This is reflected in Minnesota’s other notable distinction in Urban’s model; it had the lowest undercount (2.44 percent) in the nation.

TABLE 1

In Urban's Simulated 2020 Census, the US Population Had a Net Undercount of 0.5 Percent

Estimated 2020 Census overcounts, undercounts, and net miscounts by state

State	Official count (2020 Census)	Hypothetical full count (Urban)	Overcount (Urban)		Undercount (Urban)		Net miscount (Urban)	
			Estimate	Percent	Estimate	Percent	Estimate	Percent
Total	331,449,281	333,132,506	11,895,454	3.57	-13,578,679	-4.08	-1,683,225	-0.51
Alabama	5,024,279	5,057,647	185,344	3.66	-218,712	-4.32	-33,368	-0.66
Alaska	733,391	741,182	29,238	3.94	-37,028	-5.00	-7,791	-1.05
Arizona	7,151,502	7,199,551	269,135	3.74	-317,184	-4.41	-48,049	-0.67
Arkansas	3,011,524	3,034,480	114,054	3.76	-137,009	-4.52	-22,956	-0.76
California	39,538,223	39,883,320	1,485,352	3.72	-1,830,449	-4.59	-345,097	-0.87
Colorado	5,773,714	5,780,417	196,001	3.39	-202,704	-3.51	-6,703	-0.12
Connecticut	3,605,944	3,608,799	120,141	3.33	-122,996	-3.41	-2,855	-0.08
Delaware	989,948	992,287	35,658	3.59	-97,997	-3.83	-2,339	-0.24
DC	689,545	703,955	28,554	4.06	-42,963	-6.10	-14,410	-2.05
Florida	21,538,187	21,745,120	803,725	3.70	-1,010,658	-4.65	-206,933	-0.95
Georgia	10,711,908	10,836,346	411,103	3.79	-535,541	-4.94	-124,438	-1.15
Hawaii	1,455,271	1,465,761	54,122	3.69	-64,612	-4.41	-10,490	-0.72
Idaho	1,839,106	1,835,144	59,212	3.23	-55,250	-3.01	3,962	0.22
Illinois	12,812,508	12,837,148	440,428	3.43	-465,068	-3.62	-24,640	-0.19
Indiana	6,785,528	6,780,136	222,150	3.28	-216,758	-3.20	5,392	0.08
Iowa	3,190,369	3,173,935	102,196	3.22	-85,762	-2.70	16,434	0.52
Kansas	2,937,880	2,934,731	99,855	3.40	-96,706	-3.30	3,149	0.11
Kentucky	4,505,836	4,507,088	147,909	3.28	-149,161	-3.31	-1,252	-0.03
Louisiana	4,657,757	4,710,177	179,192	3.80	-231,612	-4.92	-52,420	-1.11
Maine	1,362,359	1,366,319	47,756	3.50	-51,716	-3.79	-3,960	-0.29
Maryland	6,177,224	6,207,158	211,360	3.41	-241,294	-3.89	-29,934	-0.48
Massachusetts	7,029,917	7,037,341	237,272	3.37	-244,696	-3.48	-7,424	-0.11
Michigan	10,077,331	10,045,051	328,349	3.27	-296,070	-2.95	32,280	0.32
Minnesota	5,706,494	5,663,238	181,330	3.20	-138,074	-2.44	43,256	0.76
Mississippi	2,961,279	3,000,324	111,140	3.70	-150,185	-5.01	-39,045	-1.30
Missouri	6,154,913	6,166,464	203,762	3.30	-215,313	-3.49	-11,551	-0.19
Montana	1,084,225	1,089,265	37,241	3.42	-42,281	-3.88	-5,040	-0.46
Nebraska	1,961,504	1,955,031	65,690	3.36	-59,217	-3.03	6,473	0.33
Nevada	3,104,614	3,126,259	122,080	3.90	-143,724	-4.60	-21,645	-0.69
New Hampshire	1,377,529	1,369,876	46,565	3.40	-38,912	-2.84	7,653	0.56
New Jersey	9,288,994	9,322,947	328,230	3.52	-362,184	-3.88	-33,953	-0.36

State	Official count (2020 Census)	Hypothetical full count (Urban)	Overcount (Urban)		Undercount (Urban)		Net miscount (Urban)	
			Estimate	Percent	Estimate	Percent	Estimate	Percent
New Mexico	2,117,522	2,139,618	82,674	3.86	-104,770	-4.90	-22,096	-1.03
New York	20,201,249	20,425,887	769,813	3.77	-994,452	-4.87	-224,638	-1.10
North Carolina	10,439,388	10,519,940	390,533	3.71	-471,085	-4.48	-80,552	-0.77
North Dakota	779,094	779,105	27,499	3.53	-27,509	-3.53	-11	0.00
Ohio	11,799,448	11,780,818	389,774	3.31	-371,144	-3.15	18,630	0.16
Oklahoma	3,959,353	3,990,397	151,670	3.80	-182,714	-4.58	-31,044	-0.78
Oregon	4,237,256	4,234,697	143,637	3.39	-141,078	-3.33	2,559	0.06
Pennsylvania	13,002,700	12,978,273	430,383	3.32	-405,956	-3.13	24,427	0.19
Rhode Island	1,097,379	1,103,296	37,866	3.43	-43,782	-3.97	-5,917	-0.54
South Carolina	5,118,425	5,165,533	192,617	3.73	-239,725	-4.64	-47,108	-0.91
South Dakota	886,667	884,886	28,904	3.27	-27,122	-3.07	1,781	0.20
Tennessee	6,910,840	6,938,559	245,177	3.53	-272,896	-3.93	-27,719	-0.40
Texas	29,145,505	29,522,692	1,144,787	3.88	-1,521,974	-5.16	-377,187	-1.28
Utah	3,271,616	3,266,586	108,421	3.32	-103,392	-3.17	5,030	0.15
Vermont	643,077	646,050	21,729	3.36	-24,702	-3.82	-2,973	-0.46
Virginia	8,631,393	8,642,370	292,085	3.38	-303,062	-3.51	-10,977	-0.13
Washington	7,705,281	7,697,407	255,717	3.32	-247,843	-3.22	7,874	0.10
West Virginia	1,793,716	1,802,367	64,598	3.58	-73,250	-4.06	-8,651	-0.48
Wisconsin	5,893,718	5,859,430	192,516	3.29	-158,228	-2.70	34,288	0.59
Wyoming	576,851	578,095	20,915	3.62	-22,159	-3.83	-1,244	-0.22

Sources: Urban's Simulated 2020 Census data and the US Census Bureau's 2020 Census Total Resident Population Counts.

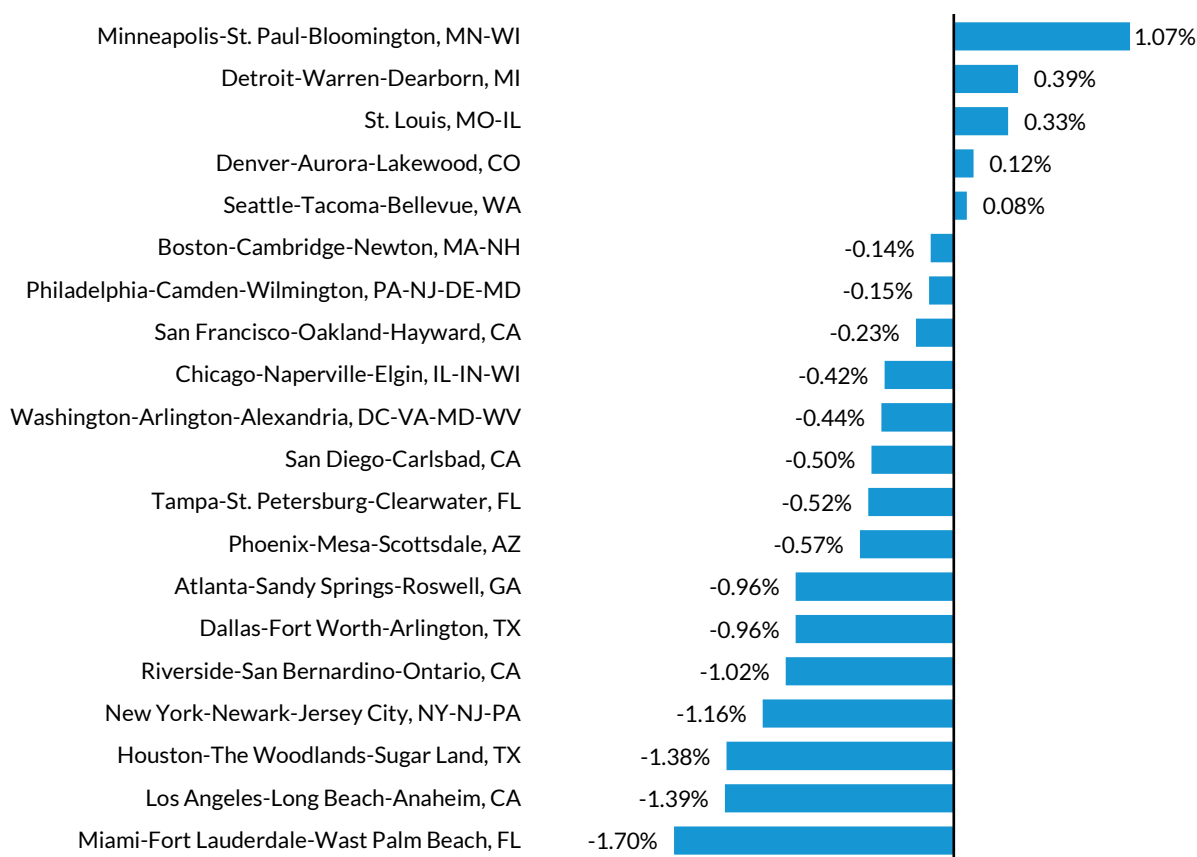
PERFORMANCE OF THE 20 LARGEST METRO AREAS IN THE 2020 CENSUS

According to Urban’s simulated 2020 Census, performance varied across different metro areas (figure 1). The outcomes in different metro areas reflect their diverse populations, as well as whether they were in areas with above- or below-average self-response rates. Minnesota and Wisconsin had above-average self-response rates and an overcount in Urban’s model, so it is not surprising that the Minneapolis-St. Paul-Bloomington, MN-WI metro area had an overcount in Urban’s model of more than 1 percent. In contrast, the Miami, Los Angeles, and Houston metropolitan statistical areas (MSAs) had the largest undercounts among the 20 largest MSAs at -1.7, -1.39, and -1.38 percent, respectively. The diversity of these metro areas’ populations, including large numbers of Hispanic/Latinx, Black, and foreign-born residents who have historically been undercounted in decennial censuses, as well as low self-response rates in the 2020 Census, culminate in higher percentages of undercounts relative to other metro areas.

FIGURE 1

The Miami Metropolitan Area Has an Undercount of More Than 1.7 Percent

Percent of total miscounts for the 20 largest metropolitan statistical areas



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Source: Urban’s Simulated 2020 Census data.

Probable Miscounts for Major Demographic Groups in the 2020 Census

Certain demographic groups have been historically harder to count in decennial censuses than others. These groups include people of color, renters, and young children (GAO 2018). Structural inequalities often contribute to this, and the pandemic exacerbated such challenges.²⁸ Black and Hispanic/Latinx adults were hardest hit by job loss and financial hardships during the first six months of the pandemic (Karpman, Zuckerman, and Kenney 2020). Communities of color were hotspots for COVID-19 at the same time the 2020 Census was beginning field operations in earnest.²⁹ Apartment dwellers were challenging to enumerate in the 2020 Census during the pandemic because of entry restrictions and a lack of cooperation from building managers.³⁰ Government distrust was high among foreign-born communities because of politicization of the census in the years leading up to it.³¹ Considering the additional health concerns, economic and political stressors, and access challenges affecting those who are often hardest to count, it may have been even more challenging to enumerate them in 2020 amidst so much uncertainty.³²

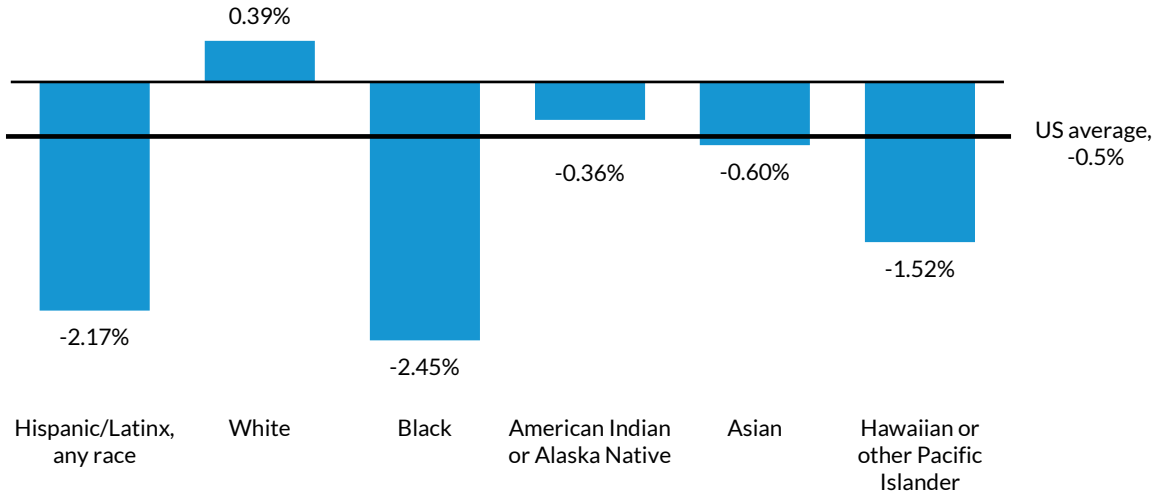
Urban's **simulated 2020 Census data** show that the demographic groups who have been historically under- and overcounted will follow those same patterns in the 2020 Census (figure 2).³³ Looking at breakdowns by racial and ethnic identification, we see that more than 2 percent of Hispanic/Latinx (2.17 percent) and Black people (2.45 percent) likely had a net undercount in the 2020 Census. In contrast, the data show that 0.39 percent of the white population was net *overcounted* in the 2020 Census. These differences in Urban's simulated 2020 Census are primarily driven by higher omissions in the data for Black and Hispanic/Latinx people relative to white people (table 2).³⁴

The implications of these miscounts are important for racial equity. Because the US has patterns of residential segregation, an undercount of Black and Hispanic/Latinx people means that the communities in which they live will miss out on their fair share of funding and resources. An overcount of white people nationwide in the 2020 Census means their communities will receive more resources than they should. This reinforces existing inequities in how health care, infrastructure, and political representation are distributed for the next decade.

FIGURE 2

More Than 2 percent of Black and Hispanic/Latinx People Were Likely Undercounted Overall

Percent of total miscounts by race and ethnicity in the 2020 Census



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Source: Urban’s simulated 2020 Census data.

TABLE 2

Undercounts Drive Net Miscounts for Key Demographic Groups

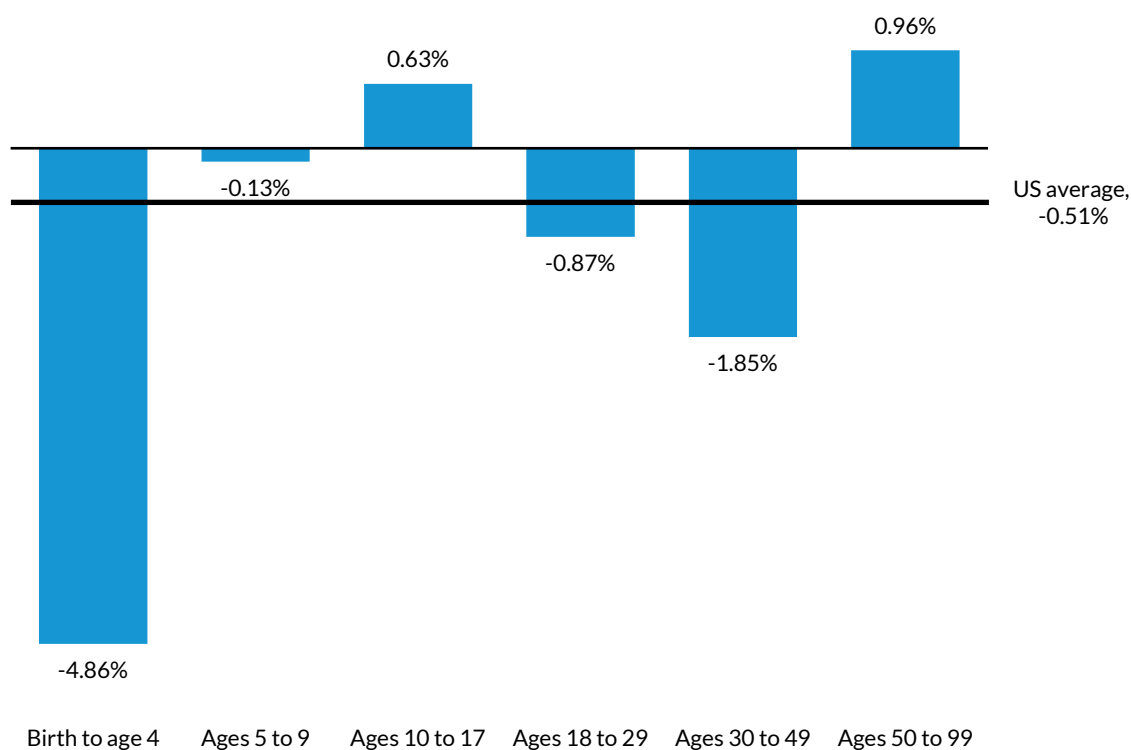
Estimated 2020 Census overcounts, undercounts and net miscounts by key demographic groups

Demographic group	Overcount (Urban)	Undercount (Urban)	Net miscount (Urban)
Total	3.57	4.08	-0.51%
Race or ethnicity			
Hispanic/Latinx, any race	4.15	6.32	-2.17%
White or other	3.21	2.82	0.39%
Black	4.46	6.91	-2.45%
American Indian or Alaska Native	4.94	5.30	-0.36%
Asian	3.44	4.04	-0.60%
Hawaiian or other Pacific Islander	4.31	5.83	-1.52%
Age group			
Birth to age 4	4.13	8.99	-4.86%
Ages 5 to 9	3.50	3.62	-0.13%
Ages 10 to 17	3.81	3.18	0.63%
Ages 18 to 29	5.00	5.86	-0.87%
Ages 30 to 49	2.93	4.78	-1.85%
Ages 50 to 99	3.25	2.29	0.96%
Housing tenure			
Owner	3.02	2.70	0.32%
Renter	4.88	7.02	-2.13%
Noncitizen in household			
No	3.46	3.51	-0.05%
Yes	4.30	7.66	-3.36%

Source: Urban’s simulated 2020 Census data.

In decennial censuses, young children have been historically undercounted, while older Americans have tended to be overcounted (King, Ihrke, and Jensen 2018; O'Hare 2015). In 2010, children younger than age 5 had the highest omission rates of any age group, which drove the undercount of young children in that census (Decennial Statistics Studies Division 2016). In Urban's simulated 2020 Census, we find that young children again were likely net undercounted at higher rates than any other age group (figure 3). We estimate that 4.86 percent of children younger than age 5 in the true US population were unlikely included in the 2020 Census. This is because young children have higher omissions, or undercounts, in the data than any other group—about 9 percent—which is not compensated for with overcounts. In contrast, nearly 1 percent of those older than age 50 were likely overcounted in the US (table 2).

FIGURE 3
Nearly 5 Percent of Children Younger Than Age 5 Were Likely Undercounted Overall
Percent of total miscounts by age group in the 2020 Census



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Source: Urban's simulated 2020 Census data.

In decennial censuses, renters have historically been among the hardest-to-count people (GAO 2018). This was likely in 2020 too; recent analyses of the 2020 Census show that census tracts with majorities of renters had an average self-response rate 10 percent lower than all others (O'Hare and

Lee 2021). Although self-response is not the only way people and households are counted in the census, it is an important marker of higher-quality data.³⁵ Urban's simulated 2020 Census data find that renters likely had a net undercount of 2.13 percent, while homeowners likely had a 0.32 percent net overcount (table 3). For renters, the net undercount was driven by high percentages of omissions, or undercounts, at 7.02 percent.

The months and years leading up to the 2020 Census were also marked by growing hostility toward foreign-born people. A chilling effect was reported among the foreign-born regarding their participation in census activities as early as 2017.³⁶ The 2020 Census was also marked by a failed attempt to add a citizenship question to it³⁷ and contributed to heightened distrust among noncitizens. Researchers estimated that adding the citizenship question led to a 2.2 percentage point drop in self-response to the 2020 Census *overall* because of omissions among households with at least one noncitizen (Brown et al. 2019). These factors all suggest that noncitizens were an especially likely undercounted group in the 2020 Census. In Urban's simulated 2020 Census, we find that those with noncitizens in the household had a probable net undercount of 3.36 percent, driven by an especially high rate of omissions (7.66 percent) (table 2). These findings reflect research finding that respondents born outside of the US were significantly more concerned than those born in the US that their answers on the 2020 Census would be used against them (McGeeney et al. 2019). Lack of trust in the US Census Bureau safeguarding their data would directly impact whether someone would willingly respond to the census.

How the 2020 Census Relates to Potential Funding and Apportionment Scenarios

The 2020 Census should be fair and accurate, not solely because data quality matters, but also because so many federal decisions critical to US democracy are built on it. The 2020 Census data are used for political decisionmaking, such as apportionment and redistricting, which determine representation at the federal and local levels for the entire following decade. Data from the 2020 Census are also used to allocate federal spending; more than 316 federal programs have their allocations determined using decennial census data in some form (Reamer 2019). Thus, ensuring the 2020 Census data are high quality matters a great deal for political and funding outcomes that affect all US residents.

Apportionment. Article 1, section 2 of the US Constitution states that an enumeration of the country should be conducted every 10 years to determine how representatives are apportioned between the states in the Union; apportionment is the reason we have a decennial census.³⁸ To determine how the 435 representatives are allocated every 10 years, the US Census Bureau uses the decennial census data to assign each state at least one representative, and the remaining 385 seats are then assigned based on

population.³⁹ Urban replicated the “method of equal proportions” used by the US Census Bureau on the simulated data (see appendix for details).

In Urban’s **hypothetical full-count** scenario, we assume that all US residents in the true population are counted once in the 2020 Census. This scenario is never likely to occur but helps us understand how an optimal census scenario would relate to apportionment. In Urban’s **hypothetical full count**, we find that only two states would have a different number of seats in the US House of Representatives than what they had in the official 2020 Census results. In this scenario, Minnesota would lose a representative (from 8 to 7) and New York would gain a representative (from 26 to 27).

Medicaid funding. In addition to apportionment, the 2020 Census is used to determine how to allocate money to federally funded programs. The amount is not trivial, either. One recent estimate found that more than 1.5 trillion dollars in federal funding is allocated to 316 programs using decennial census counts, directly and indirectly (Reamer 2019). Medicaid is one of the largest programs that uses census counts to distribute funds to states. In fiscal year 2017, Reamer (2019) estimated that federal reimbursements to the states for programs based on the FMAP formula, such as Medicaid, was more than \$405 billion.

Because Medicaid funding is such an important way in which the decennial census counts have direct relevance for states, their budgets, and their residents’ well-being, it can illustrate the impact of an incomplete count. We present findings that calculate the FMAP for each state based on our **hypothetical full-count** simulation where we assume that everyone is counted accurately and completely and compare them with the FMAP calculated with the official 2020 Census counts. The FMAP determines the percentage of a state’s Medicaid expenses that the federal government will reimburse. It is derived from understanding state per capita income relative to the national estimate and ranged from 50 to 78 percent in 2021.⁴⁰ It is important to note that our FMAP calculations are a proxy; many official data sources used by the Department of Health and Human Services to produce the official numbers are not publicly available. So we have replicated this with comparable and up-to-date data sources. See the appendix for additional information about our methodological decisions.

As the table below demonstrates, states where we estimate a net undercount would miss out on tens of millions of dollars every year in Medicaid reimbursements (table 3). Texas notably would miss an estimated \$247 million in federal reimbursements for Medicaid in 2021. This is about 1 percent of what they would be estimated to receive with their official census counts. Florida (\$88 million), Louisiana (\$46 million), Georgia (\$47 million), North Carolina (\$24 million), and Mississippi (\$20 million) are among those states that could miss out on large federal Medicaid reimbursements in 2021 because of

2020 Census undercounts. The values range from 0.26 to 0.99 percent of the total federal Medicaid reimbursements for these states.

In Urban’s simulated 2020 Census, we estimate that some states had net overcounts of their populations. These overcounts mean that in the next decade, such states will receive more federal Medicaid reimbursement money than if they had an accurate count. If each person were counted in the 2020 Census accurately, Pennsylvania would receive \$215 million *less* in Medicaid reimbursements. Ohio (\$112 million), Minnesota (\$156 million), and Michigan (\$107 million) would each receive much lower Medicaid reimbursements from the federal government, attributed to overcounts of their populations. The values range from 0.74 to 2.33 percent of the total federal Medicaid reimbursements for these states.

Of note, states with no difference in their funding under this scenario include Alaska, California, Colorado, Connecticut, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Washington, West Virginia, and Wyoming. Except for West Virginia, these states have high per capita income relative to the national per capita income, which means they routinely do not qualify for reimbursements above the 50 percent minimum for reimbursements. This would not change in a hypothetical full count either.

TABLE 3
Some States Miss Out on Millions of Federal Reimbursement Dollars by Not Counting All Residents
Estimated 2021 federal reimbursements for Medicaid to states, based on the FMAP (millions of dollars)

State	Federal Medicaid reimbursements using official census count (\$ millions)	Federal Medicaid reimbursement using hypothetical full count (\$ millions)	Difference in what states would receive in a hypothetical full count (\$ millions)
Total	345,744	345,263	-481
Alabama	4,318	4,323	5
Alaska	1,057	1,057	0
Arizona	8,829	8,843	14
Arkansas	4,916	4,926	10
California	44,368	44,368	0
Colorado	4,650	4,650	0
Connecticut	4,299	4,299	0
Delaware	1,331	1,326	-5
Florida	14,731	14,819	88
Georgia	7,257	7,304	47
Hawaii	1,243	1,247	4
Idaho	1,518	1,508	-9
Illinois	9,486	9,429	-57
Indiana	8,322	8,273	-49
Iowa	3,248	3,206	-42
Kansas	2,188	2,171	-18
Kentucky	7,447	7,421	-27

State	Federal Medicaid reimbursements using official census count (\$ millions)	Federal Medicaid reimbursement using hypothetical full count (\$ millions)	Difference in what states would receive in a hypothetical full count (\$ millions)
Louisiana	8,063	8,109	46
Maine	1,855	1,850	-5
Maryland	5,904	5,904	0
Massachusetts	8,811	8,811	0
Michigan	11,909	11,802	-107
Minnesota	6,688	6,533	-156
Mississippi	4,290	4,310	20
Missouri	6,821	6,799	-22
Montana	1,206	1,206	-1
Nebraska	1,265	1,250	-15
Nevada	2,493	2,499	6
New Hampshire	999	999	0
New Jersey	8,046	8,046	0
New Mexico	3,877	3,892	15
New York	30,141	30,141	0
North Carolina	9,220	9,244	24
North Dakota	663	658	-5
Ohio	15,211	15,098	-112
Oklahoma	3,514	3,522	9
Oregon	5,566	5,522	-44
Pennsylvania	16,820	16,605	-215
Rhode Island	1,457	1,458	1
South Carolina	4,559	4,575	16
South Dakota	521	515	-5
Tennessee	6,862	6,856	-7
Texas	24,868	25,115	247
Utah	1,808	1,795	-13
Vermont	962	961	-1
Virginia	5,760	5,718	-42
Washington	7,480	7,480	0
West Virginia	2,932	2,932	0
Wisconsin	5,667	5,588	-78
Wyoming	297	297	0

Sources: US Bureau of Economic Analysis State Annual Personal Income 2020 (Preliminary), Urban’s hypothetical full-count data, and the US Census Bureau’s 2020 Census Total Resident Population Counts.

Notes: Estimates are subject to rounding; the “Difference” column may be +/- 1 as a result. The District of Columbia is not included because its FMAP reimbursements are fixed.

Medicaid is a straightforward example that illustrates how the census impacts federal funding allocations to states because its formula directly uses population counts. In contrast, most other federal funding allocations rely on counts by characteristics such as age or income to determine a more selective population of eligibility (Reamer 2018). Consequently, our example may understate the full effect an undercount could have on a community’s funding. For example, we know that children younger than age 5 have historically been undercounted (O’Hare 2015). In Texas, the undercount of young children was likely much higher than in most other states (Elliott et al. 2019). Federal funding allocations

based on counts of young children will further disadvantage those in Texas, relative to other states, over the next decade.

Data Considerations

This study is based on the best data available and is grounded in robust projections and microsimulation methodologies. However, there are important limitations in our analyses and the assumptions we make to produce these data. We feature overarching considerations here.

Our projections of the population used the best data sources available, but they have limits. Our estimates of the census’s accuracy rely on data with distributions of individual and household characteristics of states and geographical areas. Such characteristics include age, race, ethnicity, citizenship, whether households are rented or owned, and local rates of self-response to the 2020 Census. The 2015–19 American Community Survey (ACS) has data on most of these characteristics, but these data are themselves subject to error and require projection methods to mature the population to Census Day. The data sources we used to calibrate the “maturing” of the population—namely the Census Bureau’s 2020 Demographic Analysis and the 2020 Census itself—provided counts for the national age distribution in 2020 and state population totals in 2020, respectively, but did not provide information on all population characteristics we projected at the state level and are themselves subject to uncertainty. As new information is made available and incorporated in our models, it will be possible to further calibrate our estimates of the starting population on Census Day 2020.

Our models of the 2020 Census data’s accuracy are based on the 2010 Census and follow-up surveys. We know that population shifts from 2010 to 2020 included some characteristics associated with lower census accuracy in 2010 (such as an increased share of renter households), as well as some characteristics associated with higher census accuracy in 2010 (such as an increased share of people ages 50 and older). However, we cannot know the relationships between these population characteristics and the 2020 Census’s accuracy until the Census Bureau releases findings from the 2020 PES. Further, there are reasons to anticipate that some relationships between population characteristics and census accuracy will have changed amid the new circumstances of the 2020 Census. For example, the shift from mail to internet as the primary mode of self-response will likely change the relationship between Census accuracy and household renter or ownership status.

Our models of the 2020 Census data’s accuracy assumed no interactions between different population characteristics. We know that multiple population characteristics affect census accuracy, but past postcensus surveys such as the PES do not have the precision for estimating the degree of

overlap of those characteristics. For example, part of the reason US people older than 50 had relatively high rates of census representation in 2010 was that they tended to live in owned rather than rented households. But the 2010 PES did not have the large sample sizes necessary to estimate how much the variation in census accuracy by age was *because* of homeownership, for example. The appendix includes details about the process for creating the study’s models of census accuracy across multiple individual and household characteristics.

Some factors new to the 2020 Census were not incorporated in these analyses. Our data on census accuracy are derived from the 2010 Census. As additional data are released about the 2020 Census’s performance, we will seek to incorporate additional factors in future analyses, including the following:

- More than half of all households responding to the 2020 Census did so via the internet.⁴¹ How accurate were the responses of households who completed the census online rather than by other modes? How did online responses affect differences in census accuracy by characteristics of individuals and households (age, household tenure, citizenship, race and ethnicity, and new factors such as household income)?
- How did changes in the questions, new coding rules, and innovations in the use of administrative records for imputation of missing data⁴² affect differences in census accuracy by characteristics of individuals and households (age, household tenure, citizenship, race and ethnicity)?
- How did the special circumstances and population movements of the pandemic affect census accuracy? For example, were challenges encountered enumerating the group quarters population—particularly the college and university student housing population (GAO 2021)—important for the count’s accuracy?
- Did political division and government distrust affect 2020 Census participation and accuracy for different demographic groups and geographic regions?

Because of these cited assumptions, the data we produce will not match the official estimates precisely—including those for states, metro areas, and demographic groups—and could be subject to future revisions as new data become available. All data-collection endeavors, including the decennial census, are imperfect; the “true” number cannot be known. The 2020 PES and various data-quality measures released by the US Census Bureau over time will shed light on some of these questions. For now, we urge caution in interpreting these results, because we cannot yet account for the aforementioned factors.

Conclusion

Counting the US population every decade is an extraordinary effort. Years of research and planning go into its execution on Census Day on April 1st at the start of each new decade. Typically, the decennial census happens in predictable environments, and plans made by the US Census Bureau proceed accordingly. This was not the case in 2020. The 2020 Census was conducted during a pandemic and amidst politicization of its scientific work—threats to its execution not previously encountered. Although no census is perfect, questions and concerns have been raised about the quality of the 2020 Census and whether the data will be as accurate as previous censuses (GAO 2020c; Thompson 2021). The goal of Urban’s study was to address such questions about quality and provide additional data about the 2020 Census’s accuracy and fairness.

Our simulation of the 2020 Census finds there was likely an overall 0.5 percent net undercount of the US population. Although this is different from the 2010 count, which had near-perfect net accuracy, it is perhaps not as severe an undercount as some have feared.⁴³ Net accuracy is important, but fairness also matters for the 2020 Census. We see considerable variation in who was undercounted and overcounted overall in the 2020 Census. We find that the true total population of Mississippi and Texas were undercounted in our simulated 2020 Census by 1.3 and 1.28 percent, respectively, while Minnesota was net overcounted by 0.76 percent. Such differences matter for these states for the next decade, as Mississippi and Texas residents will receive less of their fair share of federal funding for infrastructure, health care, and children’s programs, while Minnesota residents will receive more. For example, we find in our simulations that if residents had been counted accurately in the 2020 Census, Texas would receive over \$247 million more and Minnesota would receive \$156 million less federal Medicaid reimbursements in 2021. This illustrates the impact that a fair and accurate census has on people’s well-being and how disparate these outcomes can be across the nation.

Similarly, we find that groups hardest to count in recent decennial censuses again were likely undercounted in the 2020 Census. Black and Hispanic/Latinx people had a net undercount of more than 2.45 and 2.17 percent, respectively, in our simulated 2020 Census. Young children, or those younger than age 5, were likely net undercounted by 4.86 percent. Nationwide, renters were likely undercounted by 2.13 percent overall, and households with a noncitizen present were likely undercounted by 3.36 percent overall. For these groups, equity issues arise—not only with the count’s fairness, but also with how resources will be distributed and who will miss out on their fair share of political representation and funding.

It is impossible to change the outcomes of the 2020 Census, but with adequate planning and innovation, the 2030 Census can be improved for the hardest-to-count groups and places. First, future operational changes should be researched to better understand if their implementation will adversely affect enumerating the hardest to count. The expanded use of administrative records, for example, may not improve the enumeration of the hardest to count if they are also more likely to be missing from those data sources (McClure, Santos, and Kooragayala 2017). Second, states and cities should be supporting efforts to count their communities as completely as possible. Some have argued that Arizona, Florida, and Texas could have lost potential seats in the US House of Representatives, in part, because they did not sufficiently promote the census.⁴⁴ Promoting participation in the 2030 Census will benefit all states, cities, and residents within them. Third, adequate funding for the census matters—not simply in the years where fieldwork is executed in earnest—and should be consistent and strong in early years when testing and planning for innovations occur.⁴⁵ These efforts are all possible but require us to collectively recognize how critical it is to invest in the decennial census and value it as a core component of our democracy.

The 2020 Census may have happened in an anomalous year. There may never be another census conducted amidst attempts to politicize it and as the country shuts down because of a pandemic. What is known, however, is that fully counting the nation's population is becoming increasingly complicated. Innovations are needed to better understand the quality of the census count, its fairness, and its implications for the following decade. One potential innovation is Urban's microsimulation model, which offers insights on the quality of the decennial census from a data source external to the US Census Bureau. Through our simulated 2020 Census, we provide an important evidence-based benchmark to better understand the decennial census's performance. Over the next decade, refinements made to this model and new techniques from other researchers—both within and external to the US Census Bureau—will become increasingly important tools to ensure that our once-a-decade enumeration withstands threats and challenges to its quality in an increasingly complex nation.

Appendix. Detailed Methodology

To best understand the possible under- and overcounts in the 2020 Census, we created data in a two-part process. First, we created a dataset with projections of the US population to April 1, 2020, and then used those data to create a microsimulation model. Below we explain these processes, assumptions, and scenarios for apportionment and Medicaid funding that we applied to the data.

Developing 2020 Population Estimates

We generated Census Day 2020 population estimates by geography, age group, race and ethnicity, presence of noncitizens in the household, and household ownership or renter status, for the US Household Resident Population for April 1, 2020 (Census Day). These population estimates provide the foundation for projecting 2020 undercounts. The following definitions were used in generating the 2020 population estimates.

Race and ethnicity. For this study, we applied a “bridged race” approach to specifying race categories that correspond with the race specifications used in the 2010 Census Coverage Measurement (CCM) study—our data source for historical miscounts in the census (Keller and Fox 2012; Mule 2012).⁴⁶ To be consistent with racial and ethnic categories published in the CCM, we produce population projections for the total population and the following categories: Hispanic/Latinx (all races), white (non-Hispanic/Latinx), Black (non-Hispanic/Latinx), American Indian and Alaska Native (non-Hispanic/Latinx), Asian (non-Hispanic/Latinx), and Hawaiian/Pacific Islander (non-Hispanic/Latinx).

Age. Age is identified in single years of age; then grouped into categories used in the 2010 CCM study: from birth to age 4; ages 5 to 9, 10 to 17, 18 to 29, 30 to 49, and 50 and older.

Geography. Geography is identified at the state level and at the level of 2012-defined Public Use Microdata Areas (PUMAs.) To merge and present information, we also identified the county of residence and metropolitan area of residence, if applicable.

Household tenure. All individuals residing in households are identified as living in one of two kinds of households: those owned or mortgaged versus those rented. Group quarters populations are an additional category not included in the census accuracy estimates.

Citizenship. All individuals are identified into two categories related to citizenship status: US-born and naturalized citizens or noncitizens. All individuals are also identified as either living in a household with at least one noncitizen or living in a household of only citizens.

Methodology for Creating Census Day Population Estimates

Data. The core dataset for our microsimulation model is the 2015–19 combined American Community Survey (ACS), with a total of 15,947,000 person-level cases. The 2015–19 ACS has a set of analytic weights that sum to 324,697,795 million US residents, so each “case” in the sample can be thought of as a weighted entity representing about 20 US residents. The procedure for estimating the Census Day population involved adjusting the person-level analytic weights for each case to project to April 1, 2020, using the procedure described below. No person-level cases were added or subtracted from the ACS dataset during the population estimation procedure—only the person weights were adjusted.

We used respondents’ detailed race self-reports in the ACS, including self-reports of multiple races, “other race,” and missing data on race to assign all cases to a limited set of racial and ethnic categories. We imputed categories for those missing race data. Each case with a “multiple race” response was allocated to a single racial/ethnic category, based on bridged race-allocation ratios (Liebler and Halpern-Manners 2008) and assignment according to a random draw from a uniform linear distribution. The categories we assigned are as follows:

- Hispanic/Latinx ethnicity, any race selected
- non-Hispanic/Latinx ethnicity, white
- non-Hispanic/Latinx ethnicity, Black
- non-Hispanic/Latinx ethnicity, American Indian and Alaska Native
- non-Hispanic/Latinx ethnicity, Asian
- non-Hispanic/Latinx ethnicity, Hawaiian and Pacific Islander

We used the ACS person-level citizenship identifier and the household roster for each household to develop an indicator of whether a person coresided with noncitizens in the same household.

We imputed county of residence from the PUMA variable. For instances where multiple counties make up a single PUMA, we imputed county using probabilities based on a synthetic weighted total

population average of the multiple counties. (We used this information to impute census self-response rates in the respondent's county of residence.)

Projection procedure. We used Demographic Analysis (DA) Population Estimates (Jensen et al. 2020), with populations by single years of age, to calibrate and mature the US population weights from those provided in the 2015–19 ACS dataset to the US Census Bureau estimates for April 1, 2020. Note that these Census Day population estimates were created before the release of any actual 2020 Census counts. We also incorporated separate adjustments by state so the population estimates were consistent with the actual 2020 Census apportionment counts by state. To calibrate our simulated population totals so the simulated census count would match the actual census count for each state, we created a weighting adjustment equal to the ratio of each state's simulated census count to that state's actual census count and applied that adjustment to each simulated person in the state. This adjustment turned out to be minor. Our initial estimation of the census count was about 0.15 percent smaller than the actual census count, so this additional adjustment had the cumulative effect of increasing the estimated person weights for the entire US population by 0.15 percent.

Explaining the Microsimulation Model through Examples

The crux of this project and its analysis is tied to Urban's creation of a microsimulation model to understand the accuracy (with our simulated 2020 Census) and fairness (with our hypothetical full count) of the 2020 Census. As described in the report, a microsimulation model is a computer program that mimics the operation of government programs on individual members of a population. In our study, we use our **simulated 2020 Census scenario** to understand likely over- and undercounts in the 2020 Census for the US population. We account for previous data on these patterns, including from the 2010 Census, the 2010 PES, and other census and expert research. In these data, each individual result is multiplied by whatever "weight" is associated with the unit in the survey data. The weighted individual results are added together to obtain aggregate results, which in this study reflect the population of the US and different groups' likelihood of being overcounted or undercounted in the 2020 Census. We then take these data to create a **hypothetical full-count scenario** to explore what a fair count would look like for the US if every person were counted and likely outcomes for apportionment and the allocation of federal Medicaid funding.

The following example walks through the process for how a simplified computer program would be designed to determine if a person would be counted more than one time in the 2020 Census. This example is a simplification of our full methodology, which is described in more detail in the following

section. Let's assume that we have a population drawn from the most recent ACS data containing information about each person with at least the following variables for adults: gender, age, marital status, number of children, and a measure of family income.

The first step would be to determine the target number of people counted more than once. We might, for example, take the rates from tables provided by the self-reported response rates in the census. Using this rate and multiplying by the corresponding number of people in our survey in the same group, we would arrive at the target number of people enumerated twice that we need to simulate to match this assumed rate. For example, using a simple rate of 10 per 1,000 people, if we only had 100 people, we would expect one person to be counted more than once. If we had 10,000 people, we would expect 100.

Next, we develop a model to calculate the probability that a person is counted multiple times in the 2020 Census. Suppose for our example's sake that this probability is calculated via an equation and has values somewhere between 0.015 and 0.03. The table below shows a very simplified example of what might be calculated for 10 people.

TABLE A.1
Microsimulation Example, Based on Survey Data

Person ID	Probability of being enumerated twice in 2020		Probability: random number
	Census	Uniform random number	
1	0.015	0.1830	-0.1680
2	0.026	0.7156	-0.6896
3	0.030	0.7010	-0.6710
4	0.022	0.6304	-0.6084
5	0.016	0.9937	-0.9777
6	0.015	0.7722	-0.7572
7	0.018	0.0142	0.0038
8	0.027	0.1376	-0.1106
9	0.015	0.3259	-0.3109
10	0.028	0.8894	-0.8614

The last step is to use a uniform random number drawn for each person for this event to choose the people who will be selected as counted twice.

There are many ways this can be done. In a pure Monte Carlo simulation, we would choose the people for whom the probability of being counted twice is greater than or equal to a random number. In this case, that would simply be one person: Person ID 7.

If we want to hit the target rate exactly, we could calculate the expected number of people we want to select, sort by the difference between the probability and the random number, and choose the

expected number of people to count twice. If the model has been calibrated well, then running without this alignment should produce results very close to those using the targets.

Alternately, we could use weights, as we do in practice in this model and describe below. This weight can be adjusted to hit the targets. Again, if calibrated and performing well, the model will produce similar results with and without alignment to targets.

Methodology for the 2020 Census Miscount Scenarios

The 2020 Census miscount analysis allows users to examine rates of erroneous enumerations (counts of one person incorrectly identified as two) and of omissions (counts of one person incorrectly identified as zero people, grouped according to geographic areas and demographic and household characteristics).

Simulated 2020 Census: Estimates of Census Accuracy

We estimated the 2020 Census counts using a procedure that assigned each case in our population dataset to a census outcome of accurately counted, omitted (i.e., not counted), or erroneously enumerated (i.e., a person counted that was either a duplicate or otherwise associated with a count that should not have been made, such as a child born on April 2, 2020, or later). The sum of such assignments, weighted by the appropriate estimated person weights, resulted in weighted estimates of the census count for each geographic area and for each demographic subpopulation within a demographic area.

Each case in the weighted sample is assigned a probability of an erroneous enumeration according to the following stepwise process.

STEP 1: ADJUSTING FOR COUNTY CENSUS SELF-RESPONSE RATES:

In the first step, the county-specific percent self-response rate for each case is identified using 2020 Census data on county-specific self-response rates⁴⁷ and matched to the case's PUMA using crosswalk files from the Missouri Census Data Center.⁴⁸ Using estimates from 2010 Census PES Data (US Census Bureau 2016), each case is given an initial probability of being erroneously enumerated or omitted according to the following formula:

First-step probability of erroneous enumeration =

$P(\text{erroneous enumeration, conditional on self-responding household in 2010}) * (\text{county proportion self-responding in 2020 Census})$

+ $P(\text{erroneous enumeration, conditional on not self-responding household in 2010}) \times (1 - \text{county proportion self-responding in 2020 Census})$

First-step probability of omission =

$P(\text{omission, conditional on self-responding household in 2010}) \times (\text{county proportion self-responding in 2020 Census})$

+ $P(\text{omission, conditional on not self-responding household in 2010}) \times (1 - \text{county proportion self-responding in 2020 Census})$

STEP 2: ADJUSTING FOR PRESENCE OF NONCITIZENS IN THE HOUSEHOLD

In the second step, all cases are identified as either residing in a household with only citizens or residing in a household with at least one noncitizen.

Each case has its probability of an omission adjusted according to the estimated probabilities reported by Brown and colleagues (2018) for being omitted from the American Community Survey if one resides in a household with only citizens or in a household with at least one noncitizen, respectively.

To avoid overcounting the probability of omission because of the correlation between county self-response rates and presence of noncitizens in the household, we summarize the first step probability of omission at the population level based on the county distribution of cases residing with only citizens and the county distribution of cases residing with at least one noncitizen, respectively.

Second-step probability of erroneous enumeration =

$P(\text{erroneous enumeration, conditional on whether there are noncitizen residents in the household})$

+ First-step probability of erroneous enumeration, conditional on county self-response rate

- Adjustment for population correlation between noncitizen residents in household and county self-response rate

Second-step probability of omission =

$P(\text{omission, conditional on whether there are noncitizen residents in the household})$

+ First-step probability of omission, conditional on county self-response rate

- Adjustment for population correlation between noncitizen residents in household and county self-response rate

STEP 3: ADJUSTING FOR HOUSEHOLD TENURE

In the third estimation step, all cases are identified as living in an owned or rented household (cases in group quarters settings are not given any adjustments) and have their probabilities of incorrect census

counts adjusted according to estimated omission and erroneous enumeration rates from the 2010 Census (Mule 2012).

Third-step probability of erroneous enumeration =

$P(\text{erroneous enumeration, conditional on whether there the case is in an owned or rented household})$
+ Second-step probability of erroneous enumeration, conditional on county self-response rate and noncitizen households in residence
- Adjustment for population correlation between household tenure and second-step probability of erroneous enumeration

Third-step probability of omission =

$P(\text{omission, conditional on whether there the case is in an owned or rented household})$
+ Second-step probability of omission, conditional on county self-response rate and noncitizen households in residence
- Adjustment for population correlation between household tenure and second-step probability of omission

STEP 4: ADJUSTING FOR RACE AND ETHNICITY

In the fourth estimation step, all cases are identified by combined racial and ethnic group and have their probabilities of incorrect census counts adjusted according to estimated omission and erroneous enumeration rates from the 2010 Census (Mule 2012).

Fourth-step probability of erroneous enumeration =

$P(\text{erroneous enumeration, conditional on racial and ethnic group})$
+ Third-step probability of erroneous enumeration, conditional on county self-response rate, noncitizen households in residence, and household tenure
- Adjustment for population correlation between racial/ethnic group and third-step probability of erroneous enumeration

Fourth-step probability of omission =

$P(\text{omission, conditional on racial and ethnic group})$
+ Third-step probability of omission, conditional on county self-response rate, noncitizen households in residence, and household tenure
- Adjustment for population correlation between racial/ethnic group and third-step probability of omission

STEP 5: ADJUSTING FOR AGE GROUP

In the fifth estimation step, all cases are identified by age group and have their probabilities of incorrect census counts adjusted according to estimated omission and erroneous enumeration rates from the 2010 Census (Mule 2012). In addition, because of known correlation between errors in census counts

for the 0–4 age group and in postenumeration survey counts for the 0–4 age group, an additional 3.9 percent is added to the omission rate for the 0–4 age group (O’Hare 2015).

Fifth-step probability of erroneous enumeration =

$P(\text{erroneous enumeration, conditional on age group})$
+ Fourth-step probability of erroneous enumeration, conditional on county self-response rate, noncitizen households in residence, household tenure, and racial/ethnic group
- Adjustment for population correlation between age group and fourth-step probability of erroneous enumeration

Fifth-step probability of omission =

$P(\text{omission, conditional on age group})$
+ Fourth-step probability of omission, conditional on county self-response rate, noncitizen households in residence, household tenure, and racial/ethnic group
- Adjustment for population correlation between age group and fourth-step probability of erroneous enumeration

STEP 6: ASSIGNMENT OF DISCRETE CENSUS COUNT OUTCOMES

As of step five, every case of the 15.947 million person records in our reweighted ACS microsimulation dataset has a probability of an erroneous enumeration and a different probability of an omission. As a final sixth step in this microsimulation implementation, each case is assigned a random draw from a uniform linear distribution between 0 and 1, and then assigned a count of 0 (omission), 1 (accurately counted), or 2 (erroneously enumerated) based on their random draw compared with their probabilities of erroneous enumeration and omission.

Finally, these results were then calibrated (or “raked”) to the US Census Bureau’s official 2020 Census counts to derive the probabilities of miscounts among different groups.

Hypothetical Full-Count Scenario Methodology: Comparison with a Fair Census

There are two important ways to estimate census quality: through (1) *accuracy*, or the correspondence of the overall count to the true overall population, and (2) *fairness*, or whether different groups and geographic areas have similar outcomes. Our simulated 2020 Census scenario described above assesses accuracy, so to assess fairness we developed a hypothetical full-count scenario for comparison purposes in which rates of erroneous enumerations and omissions are essentially zero for all people. This is Urban’s measurement of the true US population. From the six-step methodology described above, that means that in the hypothetical full-count census scenario, each case in the entire simulation is counted once.

Apportionment Analysis

The apportionment of the 435 US House of Representative seats is determined every 10 years based on resulting state-level population counts from the decennial census. It is a key function of the decennial census; apportionment counts are the first release of data every decade, typically presented to the US President on December 31 of a census year. Because of pandemic-related schedule delays, the 2020 apportionment counts were delivered on April 26, 2021.⁴⁹

Apportionment is based on the Method of Equal Proportions, adopted by Congress in 1941. Under this approach, the first 50 seats are assigned—one to each state—and the remaining 385 seats are then allocated using an iterative process using *priority values*.⁵⁰

$$V = \frac{P}{\sqrt{n(n-1)}}$$

In this formula, V represents a priority value; P represents a state's apportionment population; and n represents the number of seats a state would have if it gained one seat. Because every state receives at least one seat, calculations begin with $n = 2$. Consequently, in its first iteration the priority value for each state's second seat would equal its apportionment population divided by the square root of $2(2-1)$. The calculations are then repeated for each value from $n = 2$ through $n = 70$. The value 70 is used for convenience because no state has more than 60 seats. The resulting values (with associated states) are then assembled and ranked to reveal the largest 385 values. This ranking determines which states receive the remaining seats.

Funding Analysis and Hypothetical Full-Count Scenario

Overall, 316 federal programs encompassing more than \$1.5 trillion use census counts in formulas that allocate funding to different geographies, largely to states (Reamer 2019). Many funding formulas are complex and use the census counts indirectly. But one formula, the Federal Medical Assistance Percentage (FMAP), uses population counts more directly to determine the percentage of reimbursement a state will receive on seven different federal programs, most notably Medicaid. These seven programs constituted 27 percent of census count-based funding and more than \$405 billion in fiscal year 2017, underscoring how important the FMAP and accurate census counts are for states (Reamer 2019).

The FMAP formula for a state is: $FMAP_{state} = 1 - ((\text{Per capita income}_{state})^2 / (\text{Per capita income}_{US})^2 * 0.45)$ (Mitchell 2020). Specifically, the FMAP is based on a ratio of the state's per capita income relative to the US total per capita income, which is then adjusted to ensure that no state's ratio is lower than the US ratio. Census counts matter for this process. They are the basis for the population estimates used to calculate a state's per capita income.⁵¹ In other words, a state's total personal income (obtained from sources other than the decennial census) is divided by its population estimate to determine each state's per capita income. The resulting per capita income for each state is then used in the FMAP formula. Because state incomes and populations change routinely, a new FMAP is calculated for each fiscal year.

The FMAP guides the reimbursements states receive, and there is a federally mandated range of minimum and maximum reimbursements. The minimum and maximum reimbursement rates for states range from 50 cents to 83 cents for every dollar spent on programs that use the FMAP ratio (Mitchell 2020).⁵² In FY 2021,⁵³ enhanced benefits were offered because of COVID-19, with a minimum of 65 cents and a maximum of 85 cents reimbursed for every dollar spent.⁵⁴ Put simply, if a state has an FMAP of 70 percent, then 70 cents of every dollar spent by that state on Medicaid would be reimbursed by the federal government.

For FY 2021, 13 states received the minimum reimbursements (FMAPs of 50 percent; enhanced FMAPs of 65 percent), including Alaska, California, Colorado, Connecticut, Maryland, Massachusetts, Minnesota, New Hampshire, New Jersey, New York, Virginia, Washington, and Wyoming. For states at the minimum, year-to-year changes in population counts rarely shift their FMAPs.⁵⁵ For the other states, FMAPs can vary from year to year and population counts may be important. In FY 2021, Mississippi had the highest FMAP at 77.76 percent and an enhanced FMAP of 84.43 percent.

In our report, we explore how changes in the 2020 Census count might theoretically affect each state's FY 2021 FMAP and its resulting Medicaid reimbursements. The exercise in this paper is meant to be illustrative and uses the following assumptions:

- First, we use preliminary 2020 estimates of total state income from the Bureau of Economic Analysis (BEA) rather than three-year averages of older data used in the official calculations. For example, for the official FY 2021 FMAP calculated by the Department of Health and Human Services, incomes from 2016, 2017, and 2018 from the US Bureau of Economic Analysis were averaged and used to moderate year-to-year fluctuations (Mitchell 2020).⁵⁶ We opt to use the more recent 2020 preliminary estimates in our analysis.
- Second, we produce state population estimates from a unique scenario used in these analyses that assumes a hypothetical full count for the 2020 Census. To assume a hypothetical full

count, we eliminate any probabilities of overcounts or undercounts for the entire US population as determined through our simulated 2020 Census count. Thus, we assume everyone in the US would be counted accurately and only once.

- Third, the FMAP is then calculated using both sets of population counts, including the recently released census total resident population counts and Urban’s estimates of a hypothetical full count for the 2020 Census. State and national estimates from the official 2020 Census counts and the hypothetical full count are used in the FMAP per capita income calculations.
- Finally, we apply the new FMAPs to the most recent data on Medicaid spending for each state from 2019, the most recent data available. This final step illustrates the differences in reimbursements each state could hypothetically receive in FY 2021.⁵⁷
- Of note, we do not include additional adjustments to the FMAP, such as those for COVID-19, or other state-specific income- or employer-based considerations.⁵⁸

The resulting findings are instructive as to how population counts—particularly if they were fairer in the 2020 Census—would theoretically affect federal funding allocations to the states.

Notes

- ¹ See “History: 1990 Overview,” US Census Bureau, accessed September 27, 2021, https://www.census.gov/history/www/through_the_decades/overview/1990.html.
- ² See also Mule (2012). Specifically, the 2010 Census had 10 million erroneous over-enumerations, which were mostly the same individuals duplicated at multiple locations. This was counterbalanced by about 10 million people omitted on net.
- ³ “2020 Census Quality and Data Processing Press Kit,” US Census Bureau, last updated September 3, 2021, <https://www.census.gov/newsroom/press-kits/2021/2020-census-quality-and-data-processing.html>.
- ⁴ Federal funding allocation for more than 100 programs, including Medicaid, Head Start, block grant programs for community mental health services, and the Supplemental Nutrition Assistance Program depend on census population counts. See Hotchkiss and Phelan (2017).
- ⁵ The state of Alabama challenged the Census Bureau’s policy of counting all US residents in 2018: “Alabama v. United States Department of Commerce,” Brennan Center for Justice, accessed September 27, 2021, <https://www.brennancenter.org/our-work/court-cases/alabama-v-united-states-department-commerce>.
- ⁶ Urban analyzed demographic trends in IPUMS (Integrated Public Use Microdata Series) data: “US Census Data for Social, Economic, and Health Research,” IPUMS USA, accessed September 27, 2021, <https://usa.ipums.org/usa/>.
- ⁷ “US Census Data for Social, Economic, and Health Research,” IPUMS USA.
- ⁸ “US Census Data for Social, Economic, and Health Research,” IPUMS USA.
- ⁹ Center for Survey Measurement, “Respondent Confidentiality Concerns,” memorandum for the associate directorate for research and methodology, September 20, 2017, <https://www2.census.gov/cac/nac/meetings/2017-11/Memo-Regarding-Respondent-ConfidentialityConcerns.pdf>.
- ¹⁰ Center for Survey Measurement, “Respondent Confidentiality Concerns.”
- ¹¹ *Mathiowetz Amicus Brief* (Case 8:18), Kravitz et al. v. US Department of Commerce (2018).
- ¹² Robert Barnes and Ann E. Marimow. “Supreme Court Puts Census Citizenship Question on Hold,” *Washington Post*, June 27, 2019, https://www.washingtonpost.com/politics/courts_law/supreme-court-puts-census-citizenship-question-on-hold/2019/06/27/6b2a49cc-93cb-11e9-b570-6416efdc0803_story.html.
- ¹³ “COVID-19 Disaster Declarations,” Federal Emergency Management Agency, last updated August 20, 2021, <https://www.fema.gov/disasters/coronavirus/disaster-declarations>.
- ¹⁴ Michael Bentley, “Examining Operational Quality Metrics,” *Random Samplings* (blog), US Census Bureau, April 26, 2021, <https://www.census.gov/newsroom/blogs/random-samplings/2021/04/examining-operational-metrics.html>.
- ¹⁵ Mike Schneider, “Census Takers Worry That Apartment Renters Were Undercounted,” Associated Press, July 5, 2021, <https://apnews.com/article/lifestyle-health-coronavirus-pandemic-census-2020-government-and-politics-9aebdfb9c1b834352676d4b95f2d9ea0>.
- ¹⁶ Robert Santos and Diana Elliott, “Is It Time to Postpone the 2020 Census?” *Urban Wire* (blog), Urban Institute, March 13, 2020, <https://www.urban.org/urban-wire/it-time-postpone-2020-census>.

- ¹⁷ Diana Elliott and Robert Santos, “Unpredictable Residency during the COVID-19 Pandemic Spells Trouble for the 2020 Census Count,” *Urban Wire* (blog), Urban Institute, March 30, 2020, <https://www.urban.org/urban-wire/unpredictable-residency-during-covid-19-pandemic-spells-trouble-2020-census-count>.
- ¹⁸ US Census Bureau, “Census Bureau Statement on Redistricting Data Timeline,” press release, February 12, 2021, <https://www.census.gov/newsroom/press-releases/2021/statement-redistricting-data-timeline.html>.
- ¹⁹ “2020 Census: Tracking Self-Response Rates Map,” US Census Bureau, January 28, 2021, <https://www.census.gov/library/visualizations/interactive/2020-census-self-response-rates-map.html>.
- ²⁰ Beth Jarosz and Paola Scommegna, “Why Are They Asking That? What Everyone Needs to Know about 2020 Census Questions,” March 23, 2019, <https://www.prb.org/resources/why-are-they-asking-that-what-everyone-needs-to-know-about-2020-census-questions/>.
- ²¹ Thomas Mule, “Administrative Records and the 2020 Census,” *Random Samplings* (blog), US Census Bureau, April 1, 2021, https://www.census.gov/newsroom/blogs/random-samplings/2021/04/administrative_recor.html.
- ²² Mule, “Administrative Records and the 2020 Census.”
- ²³ Ron Jarmin, “2020 Census Processing Updates,” *Director’s Blog* (blog), US Census Bureau, February 2, 2021, <https://www.census.gov/newsroom/blogs/director/2021/02/2020-census-processing-updates.html>.
- ²⁴ The group quarters population is included in our projections, but we lacked data to parse out changes for this group separately over the past decade.
- ²⁵ US Census Bureau, “2020 Census Apportionment Results Delivered to the President,” press release, April 26, 2021, <https://www.census.gov/newsroom/press-releases/2021/2020-census-apportionment-results.html>.
- ²⁶ US Census Bureau, “Census Bureau Releases Estimates of Undercount and Overcount in the 2010 Census,” press release, May 22, 2021, https://www.census.gov/newsroom/releases/archives/2010_census/cb12-95.html.
- ²⁷ “2020 Census: Tracking Self-Response Rates Map,” US Census Bureau..
- ²⁸ Santos and Elliott, “Is It Time to Postpone the 2020 Census?”
- ²⁹ Maria Godoy and Daniel Wood, “What Do Coronavirus Racial Disparities Look Like State by State?” NPR, May 30, 2020, <https://www.npr.org/sections/health-shots/2020/05/30/865413079/what-do-coronavirus-racial-disparities-look-like-state-by-state>.
- ³⁰ Schneider, “Census Takers Worry.”
- ³¹ Center for Survey Measurement, “Respondent Confidentiality Concerns,” memorandum for the US Census Bureau associate director for research and methodology, September 20, 2017, <https://www2.census.gov/cac/nac/meetings/2017-11/Memo-Regarding-Respondent-Confidentiality-Concerns.pdf>.
- ³² “Sworn Expert Declaration of Howard Hogan,” US District Court for the District of Maryland, Civil Action No. 8:19-CV-02710-PX, Brennan Center for Justice, September 1, 2020, https://www.brennancenter.org/sites/default/files/2020-09/Hogan_%20filed%202020-09-01_0.pdf.
- ³³ Throughout our report, the terms Black, White, American Indian and Alaska Native, Asian, and Hawaiian and other Pacific Islander all represent non-Hispanic/Latinx people. We use the shorter terms in the text and the more specific terms in the tables.
- ³⁴ There were coding changes in the US Census Bureau’s approach to race categories for this census; official 2020 Census data show that white counts were much lower than predicted and the Hispanic/Latinx and multiracial counts were much higher than predicted. It is unclear, however, how these coding changes related to patterns of

overcounts or undercounts by race and ethnicity in the 2020 Census. We assume differences exist, but at this point, we do not have enough evidence for our analysis.

³⁵ “Increasing Self-Response,” US Census Bureau, last updated May 7, 2021, <https://www.census.gov/programs-surveys/decennial-census/decade/2020/planning-management/plan/self-response.html>.

³⁶ Center for Survey Measurement, “Respondent Confidentiality Concerns.”

³⁷ Barnes and Marimow, “Supreme Court Puts Census Citizenship Question on Hold.”

³⁸ “Census in the Constitution: Why Jefferson, Madison, and the Founders Enshrined the Census in Our Constitution,” US Census Bureau, last updated March 30, 2020, <https://www.census.gov/programs-surveys/decennial-census/about/census-constitution.html>.

³⁹ Kristin Koslap and Steven Wilson, “How Apportionment Is Calculated,” *Random Samplings* (blog), US Census Bureau, April 26, 2021, <https://www.census.gov/newsroom/blogs/random-samplings/2021/04/how-apportionment-is-calculated.html>.

⁴⁰ For the duration of the pandemic, reimbursements have increased. See MaryBeth Musumeci, “Key Questions about the New Increase in Federal Medicaid Matching Funds for COVID-19,” Kaiser Family Foundation, May 4, 2020, <https://www.kff.org/coronavirus-covid-19/issue-brief/key-questions-about-the-new-increase-in-federal-medicaid-matching-funds-for-covid-19/>.

⁴¹ “2020 Census: Tracking Self-Response Rates Map,” US Census Bureau, accessed October 6, 2021, <https://www.census.gov/library/visualizations/interactive/2020-census-self-response-rates-map.html>.

⁴² Hansi Lo Wang, “What the New Census Data Can—and Can’t—Tell Us about People Living in the U.S.,” NPR, August 12, 2021, <https://www.npr.org/2021/08/12/1010222899/2020-census-race-ethnicity-data-categories-hispanic>.

⁴³ Dartunorro Clark, “Early 2020 Census Data Stir Fears of Possible Latino, Asian Undercounts,” NBC News, May 10, 2021, <https://www.nbcnews.com/politics/politics-news/early-2020-census-data-stir-fears-possible-latino-asian-undercounts-n1266633>.

⁴⁴ Dudley L. Poston and Rogelio Sáenz, “A Wasted Chance for a Third House Seat,” *The Eagle*, May 2, 2021, https://theeagle.com/opinion/columnists/a-wasted-chance-for-a-third-house-seat/article_f03b4cda-aa01-11eb-8af7-3b69fd474251.html.

⁴⁵ Diana Elliott and Charmaine Runes, “An Underfunded 2020 Census Puts an Accurate Count at Risk,” *Urban Wire* (blog), Urban Institute, March 18, 2019, <https://www.urban.org/urban-wire/underfunded-2020-census-puts-accurate-count-risk>.

⁴⁶ For person data, we used Thomas Mule (2012). For household data, we used Keller and Fox (2012).

⁴⁷ US Census Bureau, “2020 Census: Tracking Self-Response Rates Map,” accessed September 27, 2021, www2.census.gov/programs-surveys/decennial/2020/data/tracking-response-rates/self-response-rates-map/decennialrr2020.csv.

⁴⁸ “Geocorr 2018: Geographic Correspondence Engine,” Missouri Census Data Center, last updated December 4, 2018, <https://mcdc.missouri.edu/applications/geocorr2018.html>.

⁴⁹ Kristin Koslap and Steven Wilson, “Apportionment Population Counts and What to Expect on Release Day,” US Census Bureau, April 26, 2021, <https://www.census.gov/newsroom/blogs/random-samplings/2021/04/apportionment-population-counts.html>.

⁵⁰ Koslap and Wilson, “How Apportionment Is Calculated.”

⁵¹ See the definition of how the Bureau of Economic Analysis (BEA) calculates per capita income in “State Quarterly Income, 2020 (Preliminary) and State Quarterly Personal Income, 4th Quarter 2020,” BEA, news

release, last updated March 25, 2021, https://www.bea.gov/sites/default/files/2021-03/spi0321_3.pdf. Each state's total personal income is divided by its population estimate to determine per capita income. The resulting per capita income for each state is then used in the FMAP formula.

⁵² See the definition of how the BEA calculates per capita income in "State Quarterly Income, 2020 (Preliminary) and State Quarterly Personal Income, 4th Quarter 2020," BEA. Each state's total personal income is divided by its population estimate to determine per capita income. The resulting per capita income for each state is then used in the FMAP formula.

⁵³ FY 2021 spans from October 1, 2020, to September 30, 2021.

⁵⁴ See the Federal Register from the Department of Health and Human Services with published FY 2021 FMAP rates here: Federal Financial Participation in State Assistance Expenditures; Federal Matching Shares for Medicaid, the Children's Health Insurance Program, and Aid to Needy, Aged, Blind, or Disabled Persons for October 1, 2020, through September 30, 2021, 84 Fed. Reg. 66204 (December 3, 2019), <https://www.federalregister.gov/documents/2019/12/03/2019-26207/federal-financial-participation-in-state-assistance-expenditures-federal-matching-shares-for>.

⁵⁵ The District of Columbia has its FMAP federally set at 70 percent with an enhanced FMAP of 79 percent in FY 2021. See also Federal Financial Participation in State Assistance Expenditures; Federal Matching Shares for Medicaid, the Children's Health Insurance Program, and Aid to Needy, Aged, Blind, or Disabled Persons for October 1, 2020, through September 30, 2021, 84 Fed. Reg. 66204 (December 3, 2019).

⁵⁶ Preliminary state annual income from the BEA can be located here: "State Annual Personal Income, 2020 (Preliminary) and State Quarterly Personal Income, 4th Quarter 2020," BEA, news release, March 24, 2021, <https://www.bea.gov/news/2021/state-annual-personal-income-2020-preliminary-and-state-quarterly-personal-income-4th>.

⁵⁷ State Medicaid expenditure data are available here: "Total Medicaid Spending," Kaiser Family Foundation, accessed September 27, 2021, <https://www.kff.org/medicaid/state-indicator/total-medicaid-spending/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D>.

⁵⁸ See the Federal Register announcement about the FMAPs here for more information about specific adjustments that may be made to the FMAP: Federal Financial Participation in State Assistance Expenditures; Federal Matching Shares for Medicaid, the Children's Health Insurance Program, and Aid to Needy, Aged, Blind, or Disabled Persons for October 1, 2020, through September 30, 2021, 84 Fed. Reg. 66204 (December 3, 2019).

References

- ASA (American Statistical Association). 2021. "2020 Census State Population Totals: A Report from the American Statistical Association Task Force on 2020 Census Quality Indicators, Final Report." Alexandria, VA: ASA.
- Baum, Matthew A., Bryce J. Dietrich, Rebecca Goldstein, and Maya Sen. 2019. *Estimating the Effect of Asking about Citizenship on the U.S. Census: Results from a Randomized Controlled Trial*. Cambridge, MA: Harvard Kennedy School Shorenstein Center on Media, Politics, and Public Policy.
- Baumgardner, Stephanie K., Deborah H. Griffin, David A. Raglin. 2014. "The Effects of Adding an Internet Response Option to the American Community Survey." Suitland, MD: US Census Bureau.
- Brown, J. David, Misty L. Heggeness, Suzanne M. Dorinski, Lawrence Warren, and Moises Yi. 2018. "Understanding the Quality of Alternative Citizenship Data Sources for the 2020 Census." Hillcrest Heights, MD: Center for Economic Studies, US Census Bureau.
- . 2019. "Predicting the Effect of Adding a Citizenship Question to the 2020 Census." *Demography* 56 (4): 1173–94. <https://doi.org/10.1007/s13524-019-00803-4>.
- Deaver, Karen D. 2020. *Intended Administrative Data Use in the 2020 Census*. Suitland, MD: US Census Bureau, Decennial Census Programs Directorate.
- Decennial Census Management Division. 2018. *2020 Census Detailed Operational Plan for: 12. Internet Self-Response Operation (ISR)*. Suitland, MD: US Census Bureau.
- Decennial Statistics Studies Division. 2016. *Investigating the 2010 Undercount of Young Children - A New Look at 2010 Census Omissions by Age*. Suitland, MD: US Census Bureau.
- Elliott, Diana, Robert Santos, Steven Martin, and Charmaine Runes. 2019. *Assessing Miscounts in the 2020 Census*. Washington, DC: Urban Institute.
- Fernandez, Leticia, Rachel Shattuck, and James Noon. 2018. *The Use of Administrative Records and the American Community Survey to Study the Characteristics of Undercounted Young Children in the 2010 Census*. Working Paper 2018-05. Washington, DC: US Census Bureau, Center for Administrative Records Research and Application.
- GAO (Government Accountability Office). 2018. *2020 Census: Actions Needed to Address Challenges to Enumerating Hard-to-Count Groups*. Washington, DC: GAO.
- . 2020a. "COVID-19 Presents Delays and Risks to Census Count." Washington, DC: GAO.
- . 2020b. "Recent Decision to Compress Census Timeframes Poses Additional Risks to an Accurate Count." Washington, DC: GAO.
- . 2020c. *Census Bureau Needs to Assess Data Quality Concerns Stemming from Recent Design Changes*. Washington, DC: GAO.
- . 2021. *Decennial Census: Bureau Should Assess Significant Data Collection Challenges as It Undertakes Planning for 2030*. Washington, DC: GAO.
- Goldenkoff, Robert, and David A. Powner. 2018. *Continued Management Attention Needed to Mitigate Key Risks Jeopardizing a Cost-Effective and Secure Enumeration*. Statement before the House Subcommittee on Commerce, Justice, Science, and Related Agencies, Washington, DC: April 18.
- Hotchkiss, Marisa, and Jessica Phelan. 2017. *Uses of Census Bureau Data in Federal Funds Distribution: A New Design for the 21st Century*. Suitland, MD: US Census Bureau.
- Jensen, Eric B., Anthony Knapp, Heather King, David Armstrong, Sandra L. Johnson, Larry Sink, and Esther Miller. 2020. *Methodology for the 2020 Demographic Analysis Estimates*. Suitland, MD: US Census Bureau.

- Karpman, Michael, Stephen Zuckerman, and Genevieve M. Kenney. 2020. "Uneven Recovery Leaves Many Hispanic, Black, and Low-Income Adults Struggling: One in Four Adults Say Their Families Are Worse Off Six Months into the Pandemic." Washington, DC: Urban Institute.
- Keller, Andrew, and Tyler Fox. 2012. *Census Coverage Measurement Estimation Report: Components of Census Coverage for the Household Population in the United States*. Suitland, MD: US Census Bureau, Decennial Statistical Studies Division.
- King, Heather, David Ihrke, and Eric Jensen. 2018. *Subnational Estimates of Net Coverage Error for the Population Aged 0 to 4 in the 2010 Census*. Paper presented at the Annual Meeting of the Population Association of America, Denver, CO, April 26–28.
- Kissam, Edward, Richard Mines, Cindy Quezada, Jo Ann Intili, and Gail Wadsworth. 2019. *San Joaquin Valley Latino Immigrants: Implications of Survey Findings for Census 2020*. San Joaquin Valley Census Research Project.
- Konicki, Scott, and Tamara Adams. 2015. "Adaptive Design Research for the 2020 Census." Paper presented at the Joint Statistical Meetings, Seattle, WA, August 12.
- Liebler, Carolyn A., and Andrew Halpern-Manners. 2008. "A Practical Approach to Using Multiple-Race Response Data: A Bridging Method for Public Use Microdata." *Demography* 45 (1): 143–55. <https://doi.org/10.1353/dem.2008.0004>.
- McClure, Dave, Robert Santos, and Shiva Kooragayala. 2017. "Administrative Records in the 2020 US Census: Civil Rights Considerations and Opportunities." Washington, DC: Urban Institute.
- McGeeney, Kiley, Brian Kriz, Shawna Mullenax, Laura Kail, Gina Walejko, Monica Vines, Nancy Bates, and Yazmín García Trejo. 2019. *2020 Census Barriers, Attitudes, and Motivators Study Survey Report*. Suitland, MD: US Census Bureau.
- Meyers, Mikelyn. 2017. "Respondent Confidentiality Concerns and Possible Effects on Response Rates and Data Quality for the 2020 Census." Presentation given at the National Advisory Committee on Racial, Ethnic, and Other Populations Fall Meeting, Suitland, MD, November 2.
- Mitchell, Alison. 2020. "Medicaid's Federal Medical Assistance Percentage (FMAP)." Washington, DC: Congressional Research Service.
- Morris, Darcy Steeg, Andrew Keller, and Brian Clark. 2016. "An Approach for Using Administrative Records to Reduce Contacts in the 2020 Decennial Census." *Statistical Journal of the IAOS* 32 (2): 177–88.
- Mule, Thomas. 2012. *Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Persons in the United States*. Suitland, MD: US Census Bureau, Decennial Statistical Studies Division.
- O'Hare, William. 2015. *The Undercount of Young Children in the U.S. Decennial Census*. New York: Springer.
- O'Hare, William P., and Jae June J. Lee. 2021. *Who Responded in the 2020 Census? Variation in Tract Level Self-Response Rates in the 2020 U.S. Census*. Working paper. Washington, DC: Georgetown Center on Poverty and Inequality.
- Reamer, Andrew. 2019. *Brief 7: Comprehensive Accounting of Census-Guided Federal Spending (FY2017) Part A: Nationwide Analysis*. Washington, DC: George Washington University Institute of Public Policy.
- Reamer, Andrew. 2018. "Estimating Fiscal Costs of a Census Undercount to States." Washington, DC: George Washington University Institute of Public Policy.
- Santos, Robert L. 2020. "Risk Factors Affecting the Fairness and Accuracy of the 2020 Census." Statement before the House Committee on Oversight and Reform, Washington, DC, December 3.
- Thompson, John. 2021. "Understanding the Quality of the 2020 Census Is Essential." *Harvard Data Science Review* 3 (1): 1–8. <https://doi.org/10.1162/99608f92.9ce979be>.
- US Census Bureau. 2018. *2020 Census Operational Plan: A New Design for the 21st Century*. Suitland, MD: US Census Bureau.

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