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EdWorkingPaper No. 23-765

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Temporary college closures in response to the COVID-19 pandemic created an exodus of students from college towns just as the decennial census count was getting underway. We use aggregate cellular mobility data to evaluate if this population movement affected the distributional accuracy of the 2020 Census. Based on the outflow of devices in late March 2020, we estimate that counties with a college were undercounted by two percent, likely affecting Congressional apportionment. For college towns, student populations can impact government funding allocations, policy program decisions, and planning for infrastructure, public health, and more. The Census Bureau is allowing governmental entities to request count reviews through June 2023. Colleges should cooperate with state and local government efforts to ensure an accurate count.

VERSION: May 2023

Suggested citation: Andersen, Martin S., Emefa Buaka, D. Sunshine Hillygus, Christopher R. Marsicano, and Rylie C. Martin. (2023). Estimating the Impact of Temporary COVID-19 College Closures on the 2020 Census Count. (EdWorkingPaper: 23-765). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/t8y1-y046

Estimating the Impact of Temporary COVID-19 College Closures

on the 2020 Census Count

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Abstract

Temporary college closures in response to the COVID-19 pandemic created an exodus of students from college towns just as the decennial census count was getting underway. We use aggregate cellular mobility data to evaluate if this population movement affected the distributional accuracy of the 2020 Census. Based on the outflow of devices in late March 2020, we estimate that counties with a college were undercounted by two percent, likely affecting Congressional apportionment. For college towns, student populations can impact government funding allocations, policy program decisions, and planning for infrastructure, public health, and more. The Census Bureau is allowing governmental entities to request count reviews through June 2023. Colleges should cooperate with state and local government efforts to ensure an accurate count.

Keywords: Census Count, COVID-19, College Closures

The US Constitution mandates that a population census be taken every 10 years to count all people living in the United States for the purpose of reapportioning seats in the US House of Representatives (The United States Constitution, 1787). In addition to ensuring fair representation, the decennial count is used to allocate billions of dollars in federal program funds to states, counties, and cities – $1.5 trillion in federal money was distributed in 2017 alone based on the 2010 decennial census data (Reamer, 2020). Census data are also the primary source of information about the nation's population, informing planning and policy decisions about infrastructure and services such as schools, libraries, and hospitals. The US Census Bureau counted 331,449,281 people living in the United States as of April 1, 2020 (Census Day), but stakeholders have questioned the accuracy and completeness of an enumeration conducted in the midst of a global pandemic (Sullivan & Cork, 2022; Elliot, et al., 2021; O'Hare, et al., 2020; Potok, et al., 2021).

The World Health Organization declared COVID-19 a pandemic on March 11, 2020, just one day after households across the country received official Census Bureau mailings with instructions for participating in the census (Ghebreyesus, 2020). In the following weeks, state and local governments issued "stay at home"' orders, social distancing requirements, and other public health restrictions that halted government, business, and societal activities, including many census operations (Skinner, et al., 2022). Colleges across the country took additional steps to reduce COVID-19 transmission as well. On March 6, 2020, Bellevue College –a public two-year college in Washington state – became the first to announce it would transition all of its classes online; Stanford University and Touro College were the first four-year institutions to follow suit the next day (Marsicano, et al., 2020). By Census Day, 96.6% of four-year, degree-granting public and non-profit colleges and universities tracked by the College Crisis Initiative

(C2i) at Davidson College –1,393 institutions, accounting for more than 12 million undergraduate and graduate students – had announced campus closures and transitions to online education (Marsicano, et al., 2021) (Fig. 1). These closures of colleges and universities meant that millions of college students had to find other places to stay, creating potential confusion and errors in "counting everyone once, only once, and in the right place" – the mission of the 2020 Census.

There is anecdotal evidence of college towns being undercounted - several had 2020 counts that showed a decline in population since 2010 despite known student population growth (Schneider, 2021). East Lansing, Michigan, home of Michigan State, had "census tracts containing group quarters such as Fraternities and Sororities show far less population than in 2010 – even though enrollment is up and City Staff is aware that occupancy was nearly 100% on April 1, 2020" (Lahanas & City of East Lansing, 2021). Some college administrators said they mistakenly reported dorms as empty, blaming confusing or incorrect information received from Census officials (Molinaro & County of Dutchess, 2021). Other college officials reported they simply did not have the staff and time to respond to the Bureau's request for electronic transfer of student data in the midst of a public health crisis (Henderson, 2022). Unfortunately, a systematic evaluation of the impact of college closures on population counts is inherently difficult and unlikely to be quantified in currently planned data quality assessments by the Census Bureau. A 2022 report from the Office of the Inspector General found that the Bureau likely undercounted college students that lived off campus, but acknowledged it is "difficult to quantify" (Office of the Inspector General, 2022).

In this manuscript, we evaluate the potential impact of these college closures on the accuracy of the 2020 Census count. Did the exodus of college students lead to undercounts in college towns? We use a novel approach to examining the impact of college closures on population estimates, merging cellular mobility data, geospatial shapefiles, and population data to get an estimate of student movement from college campuses to other locations. We then quantify how population estimates differed based on this movement and find, for counties containing a college, that this movement reduced the average county population count by two percent of the 2020 Census count - an estimate that could have significant fiscal implications given the use of census data for the distribution of federal funds. We further show that, provided Census Bureau quality assurance measures inadequately accounted for student mobility, this movement's size and geographic distribution may have been sufficient to impact the apportionment of congressional seats.

How the Census Bureau Counts College Students

Even prior to the COVID-19 pandemic, the US Census Bureau faced unprecedented challenges in enumerating an increasingly diverse and distrustful populace. The task was made more difficult because of perpetual underfunding by Congress and political meddling by the Trump administration, including a last-minute push to add a citizenship question, a failed effort to exclude undocumented immigrants from apportionment counts, and a forced early end to the count (Hillygus & Lopez, 2020; Mervis, 2020). There were also massive disruptions in planned census operations because of the historic hurricane and wildfire season and the onslaught of COVID-19.

College students were already among the “hard-to-count” population groups; they are diverse, highly mobile, and often live in complex housing situations which makes them notoriously difficult to count. According to the Census Bureau's official residence criteria, college students should have been counted where they attend college; that is, their “usual residence" – the place they live and sleep most of the time – even if the coronavirus pandemic temporarily sent them to stay with their parents or elsewhere (United States Census Bureau, 2020). How exactly college students are enumerated, however, varies based on their living situation. College students living in dormitories are enumerated as part of a special Group Quarters operation, which counts individuals in institutional housing, such as dormitories, nursing homes, and prisons by collecting information from an institutional representative. In contrast, college students living off-campus are enumerated using household self-response; in 2020, the Census Bureau mailed households instructions to complete an online census form.

Given historically low response rates from student households, the Census Bureau had planned to conduct an early door-to-door nonresponse followup (NRFU) operation in college towns to enumerate off-campus households before students left town at the end of the semester.[1] The Census Bureau canceled early NRFU, however, choosing instead to increase the use of administrative data held by colleges and universities.[2] The Census Bureau undertook a college outreach program to request off-campus data, but less than half provided off-campus records and, even among submitted records, most provided insufficient information for identifying duplicate records (Office of the Inspector General, 2022). The potential for errors was magnified by the

[1] A total of 7.46 million households were included in the early NRFU universe that was scheduled to begin April 9, 2020. To create the early NRFU universe, Census Bureau staff identified eligible schools and the geographic area surrounding each school based on certain criteria, including the school's semester end date and the number of full-time students. Stakeholders from the regional census centers and the Federal-State Cooperative for Population Estimates reviewed and refined the early NRFU universe based on their local knowledge and research.

[2] Group Quarters enumeration also varied across schools. About half of schools had already planned to transmit student information electronically using housing administrative records. However, about 35% had planned to distribute individual Census questionnaires to students to be completed and returned to the school, which then would pass completed forms to a Census Bureau enumerator. The Census Bureau encouraged those schools to switch to the administrative-record option, with limited success.

cancellation of a census quality check process that would have historically allowed local officials to double-check data (Potok, et al., 2021).

Results

A growing body of research relies on anonymized GPS data from cellular networks to study questions about human mobility (Chen, et al., 2019; Athey, et al., 2018; Athey, et al., 2021; Chen & Rohla, 2018; Painter & Qiu, 2020; Yan, et al., 2021; Nguyen, et al., 2021; Gupta, et al., 2021; Andersen, et al., 2022; Chen & Rohla, 2018). We rely on data from Unacast, which collects and curates high-resolution location data (GPS “pings”") from applications of millions of opted-in users in an anonymized way so that we have a dataset with a unique device identifier associated with an anonymous individual, and the time, date, latitude, and longitude of the ping. We use data from February 1, 2020 to April 14, 2020 (see “Materials and Methods” in the Supplementary Materials for details). For each device and each day, we assign a “home location” to the device based on the location at which the device spent the most time. We use the term “home location” to refer to college campuses, which we mapped using a shapefile from the US Department of Homeland Security, and Census Block Groups (CBGs) for the 2020 Census – any given GPS ping is either on a college campus or in a 2020 CBG. We defined as “college” devices those that spent the plurality of the days in February on college campuses, versus other geographic areas, an operationalization that should capture students living both on and off-campus.[3] We then follow these devices from February through April 14, 2020 (two weeks after the census) to identify movement patterns for college devices and, in particular, where these

[3] Our definition of a college device may capture faculty and staff as well since they may spend the plurality of their time on campus. However, the bias introduced by this is likely to be small since we are focused on the changes in locations over time and there was no pull-factor for faculty and staff in the same way that students were “pulled” back to their parents’ homes.

devices ended up in April of 2020, restricting to devices that we observe in February and April. Some movement of devices is normal; for example, devices leave the confines of campus and head to the sites in the surrounding area (bars, restaurants, etc.) regularly on weekends before returning to their “home locations.” Devices leaving their “home locations” for an extended period of time – especially for states other than the state of the campus is unusual other than for designated breaks in instruction (spring break, summer, etc.; see Supplementary Text and Fig. S3).

Tracing these data across time (Fig. 2) finds both the typical, regularized movement associated with a normal week as well as the sharp decline once the pandemic hit. We verified that the decline in late March and April was unique to 2020 by comparing similar data for the 2018-2019 and 2019-2020 academic years (See Supplementary Information: Alternative explanations for the April decline) of the supplementary information and Fig. S3. In February of 2020, the pattern is one of stability across weeks with a decline in the average number of devices of about 40% over the weekend, versus weekdays. In early March as the COVID-19 pandemic hit, there was a sharp reduction in devices on college campuses, resulting in an 80-90% reduction in the number of devices on college campuses by late March. The decline was slightly larger for campuses without a medical school. The smaller reduction in the fraction of devices on campus for colleges with a medical school is consistent with, among other things, medical students and clinical faculty continuing to work in affiliated hospitals that are mapped as part of the same campus. As expected, these data document an outflow of devices from college campuses during the early phase of the COVID-19 pandemic that resulted in a significant decline in the number of devices on campus around the census date. We next examine where these students went when their colleges closed.

College closures might have little impact on census counts if students stayed in the same county or state – either because they moved in with friends and family locally or already lived off-campus. In assessing the quality of the census counts, what matters is not just overall accuracy of the numbers, but also their distributional accuracy (Prewitt, 2010). Because apportionment is based on population size *relative to other states*, undercounting (or overcounting) the population in one state has implications for the fair distribution of representation among all states. Fig. 3 plots the destinations and sources of college devices that left their home states. Panel A demonstrates a substantial migration of devices from other states into Illinois, in particular, although there were also large increases in population counts due to migration for New York, Georgia, and Florida. Offsetting these increases in population from college students returning home were decreases in population counts from people leaving a state (Panel B), with the largest number of people migrating out from Pennsylvania. Across our sample, approximately 19% of students traveled to a different state in April, compared to 9% in February, and the average student traveled 151 kilometers. These patterns are consistent with previously documented student enrollment and migration patterns (Kelchen & Webber, 2018).

We summarize the effect of pandemic-induced shifts of college students on census counts by constructing a counterfactual population estimate. For purposes of the counterfactual, we compute a baseline population estimate using the April locations for all devices multiplied by the national ratio of the 2020 Census count to the number of devices in our data. In the Supplementary Text we demonstrate that this estimate fits the census count well (Section: Validating Device Counts of the Supplementary Text, Fig. S1 and Table S1). We compute a counterfactual population estimate for each state by reassigning college devices to the state of their college in February of 2020 and using the same conversion ratio from devices to population. We define the pandemic-induced undercount as the counterfactual estimate (college students are assigned to their college state) minus the baseline estimate, so positive values correspond to states for which the Census undercounted the population and negative values correspond to states for which the Census overcounted the population. The net effect of the cross-state movement of devices (Fig. S4) led to a significant undercount of the state population in Pennsylvania (16,664 fewer people in the Census), but an overcount in states like Illinois (38,454), New Jersey (35,998), and Texas (22,331).

At the county-level, we computed the percentage undercount, which we defined as the undercount divided by the actual 2020 Census count. Across all counties, college counties were undercounted by approximately 2%, relative to non-college counties (see Fig. S5) for the distribution of the percentage undercount among college counties). These results were robust to a variety of alternative approaches to construct population estimates (Supplementary Text, Fig. S2 and Table S2).

Correlates of the Estimated Undercount

We assess the validity of our estimates of the gap between our mobility-adjusted population estimate and the census count by comparing the percentage difference to characteristics that are likely to be correlated with the presence of college students. Overall, counties containing a college campus were undercounted by approximately 2%, compared to counties without a college campus. If our undercount estimates reflect college student mobility, then the undercount should be larger as the share of college students increases. We assessed the correlation between the undercount that we estimated (at the county level) with characteristics of the county using data from the 2020 Census and from the 2015-2019 American Community Survey (ACS), since the latter provides more detail on demographic characteristics than are currently available from the 2020 Census. Panel A of Fig. 4 demonstrates that we find a larger (percentage) undercount in counties that reported a larger share of respondents in the ACS who were currently enrolled in college or graduate school ($\beta = 0.334, 95\%\ CI$: $[0.298, 0.369]$, $p < 0.001$). Using the group quarters detail data provided in the 2020 Census, we also find larger undercounts as the share of the population that live in a dorm ($\beta = 0.770, 95\%\ CI$: $[0.665, 0.875], p < 0.001$), live in group quarters ($\beta = 0.286, 95\%\ CI$: $[0.237, 0.334], p < 0.001$), or who are 18 or older ($\beta = 0.116, 95\%\ CI$: $[0.089, 0.144], p < 0.001$) increase. These correlations indicate that areas with a higher share of dorm residents, which are also likely to be areas with a higher share of college students, experienced a larger undercount in the 2020 Census than did areas with fewer, or no, dorm residents.

We further explored these phenomena using the age-distribution of the population in the county from the ACS. Regressing the undercount (Fig. 4, panel B) on the share of the population in various age bins (in one model) demonstrates that the undercount was positively correlated with the share of the population in the county that was 18-21 ($\beta = 0.443, 95\%\ CI$: $[0.389, 0.497], p < 0.001$) and negatively correlated with the share that was 15-17 years of age in 2015-2019 ($\beta = -0.183, 95\%\ CI$: $[-0.310, -0.056], p = 0.005$). Since most college students are between 18 and 21 years of age, a county that has a higher share of people in that age range in the ACS is also more likely to have a higher share of college students. The negative association with 15-17 year olds, who would, in 2020, be between 16 and 23 years of age is consistent with these counties being sources of college students – so this age group is a marker of college enrollment in 2019/2020.

Estimating Effects on Congressional Apportionment

Ongoing count reviews have the potential to eventually correct population counts for the purposes of some future federal funding distributions, but any undercounts of college students could still have significant consequences. Most notably, congressional apportionment has already occurred and will not be updated even if count reviews identify population errors. We thus re-estimate a hypothetical apportionment in which students do not move from their college towns to assess if the estimated errors attributed to college closures that we have identified could have impacted congressional apportionment.

To assign the 435 congressional seats to the 50 states, the US Census Bureau uses the method of equal proportions. Each state gets one seat and the remainder are assigned according to a formula based on relative population size.[4]

After accounting for the net device mobility away from college and university campuses to other states, we assessed the differences in apportionment under two scenarios – the actual count of the US Census, and a simulated count that assigns students to the state containing their college campus (i.e. their February location) rather than their April location. We assessed the simulated scenario under three counting schemes – the counterfactual estimates we report above, half of the counterfactual estimates, and double the counterfactual estimates.

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[4] States are sorted based on their priority value, which is calculated by dividing the population by the geometric mean of its current and next seats. This is shown by the equation:

$$p * 1/\sqrt{n/(n-1)}$$

where p is the state's total population and n is the number of seats a state would have if it gained a seat. Seats 51 through 435 are then distributed to states one by one based on their priority value, with the final tally for each state adding up to the number of seats they receive in the House.

Table 1 shows the changes in apportionment if college students were to be counted as residing in their institution's state. The findings suggest that the temporary movement of college students in response to college closures inappropriately shifted political power in the country. Apportionment following the 2020 Census resulted in New York losing a seat in Congress, but all of our simulated scenarios indicate that New York would not have lost a seat if college students had been correctly counted in the right location. Given the zero-sum nature of apportionment, Minnesota is the state that benefited – in all simulated scenarios, Minnesota rather than New York would have lost a seat. While the US Census Bureau conducts extensive data quality assurance, the simulated scenarios in Table 1 offer a stark demonstration of the stakes related to an accurate count of college students.

Discussion

The COVID-19 pandemic precipitated a significant relocation of millions of college students across the United States that was contemporaneous with the 2020 Census. We used individual-level data from millions of opted-in cellular devices to observe mobility patterns among college students and estimate the counterfactual Census population counts if college students had remained on campus, rather than moving to a different county. Using our main estimates, we found that in aggregate, nearly 700,000 people who normally would have been resident on a college campus moved across state lines due to the COVID-19 pandemic. The net effect of this movement was to alter state population estimates by more than 300,000 people. Our results have several implications. In this paper we demonstrate how, barring accurate quality assurance procedures, student movement theoretically could have affected the apportionment of Congressional seats. There are other potential implications that also may be affected by our results including the allocation of federal funding (Reamer, 2020).

Cellphone data has been used to estimate population distributions in countries around the world (Aiken, et al., 2022; Woods, et al., 2022; Lai, et al., 2019; Deville, et al., 2014; Aasa, et al., 2021). However, prior work has relied on call detail records that require researchers to infer user locations, which can yield divergent estimates for the population distribution (Aasa, et al., 2021). We use precise geolocation data collected from smartphone applications, so we have minimal measurement error from inferring device locations. Relative to other estimates in this literature, our approach is strongly correlated with Census estimates ($R^2 > 0.9$) and exceeds comparable estimates using more complicated methods applied to call detail records (Aasa, et al., 2021).

Our methodology has broader applications than understanding population distributions, but also allows one to estimate changes in those distributions. In our case this was due to the closure of colleges during the COVID-19 pandemic. However, other applications could include natural disasters and “routine” mobility between locations. As a result, there are applications of our approach to disaster relief, urban and transportation planning, public health, and public safety. For example, using our methodology, researchers could examine the in-flow and out-flow of people to areas affected by hurricanes or forest fires; alternatively, the same methodology could examine the ways in which people use public transportation to better understand traffic congestion for the purposes of large-scale transit planning.

Limitations

The data used in this analysis are not without limitations. It is possible that the set of people who opted in to sharing their data with Unacast differs from the population as a whole in ways that could affect our results. In the Supplementary Information we assess this possibility by incorporating Unacast's self-reported device share in each state, (see Table S1), which demonstrates that our population estimates are similar when we adjust for the Unacast share. Our estimates may also be impacted by the California Consumer Privacy Act, which proscribes additional requirements for sharing location information. Indeed, our largest estimation error in our data is in California. Reassuringly, our main results are robust to accounting for the effect of the Act and to using state-specific conversion factors. Finally, when we define home locations using time outside of the traditional work day yields similar findings as our main results. Across all of these alternative methods, we continue to find that college counties were undercounted by between 1.6 and 2.1% (Supplemental Text Table S2.).

Conclusion

When colleges across the United States closed in Spring 2020 due to the COVID-19 pandemic, few institutional leaders likely thought about the ramifications of those decisions for the US Census count. The Census Bureau had a near impossible task: account for rapid and unprecedented movement across the United States due to a pandemic event unlike any in the past 100 years. Even with its best efforts the Census may have overlooked a key demographic in its count processes –college students. Using data on 75 million mobile devices, we show the difficulty in estimating populations in college towns. We demonstrate how the exodus of students from college towns may have led to inadvertent and completely understandable miscounts. Given how razor thin the margins for Congressional apportionment were in 2020, it is unsurprising that even a minor miscount of students could have a big impact on representation. But census numbers also impact federal funding allocations, policy program decisions, and planning for infrastructure, public health, and more. Given the high stakes of the census count, municipalities and states should work with colleges to go through the Census Bureau's process for reevaluating the counts of group quarters – like college residence halls.

In particular, our results speak to the necessity for collaboration between higher education institutions and the municipalities and states in which they are located. Until June 2023, the highest elected or appointed official in tribal, state, and local governmental units (i.e. tribal areas, states, counties, cities) can request that the Census Bureau review the data used to calculate 2020 population counts through the Count Question Resolution (CQR) operation (United States Census Bureau, 2022). Under CQR operations, the Census Bureau will review boundaries or housing counts, but will not validate group quarters enumeration. If a municipal or state government wants any group quarters population data (like college and university on-campus students counts) reviewed, they must submit a case for review through the post-census group quarters review (PCGQR) operation (United States Census Bureau, 2022). The PCGQR operation, however, does not include individual housing counts and therefore will not address the potential errors associated with students that live off campus.

The processes in place for census count quality assurance require strong town/gown relationships. Local governmental officials should collaborate with colleges in the area to address any concerns around the 2020 group quarters or off-campus student population counts. Likewise, if college officials believe their student populations were undercounted, they should work with governmental units to ensure an accurate count. Accurately counting college students is a difficult task, even without the challenges posed by the COVID-19 pandemic. The Census Bureau recognized the possibility that people were miscounted during the 2020 enumeration, and have put measures in place to address potential miscounts. CQR and PCGQR will not change apportionment or redistricting, but revisions made during these two secondary reviews will inform the Population Estimates Program and allow policymakers and researchers to have higher quality data. Advocacy done at the local level can ensure that counties with colleges and universities do not miss out on potential funding opportunities for the future.

Unfortunately, there has to date been relatively little engagement with the Census' PCGQR operation. Only 31 governmental units submitted a request for a secondary review of group quarter populations as of April 24, 2023 (United States Census Bureau, 2023). Of these 31 governmental units, just over half contained a 4-year college or university (See Table S3 in Supplementary Information). For example, Dutchess County, New York specifically requested a review of the 2020 count because of unprecedented college student movement during COVID-19 and potential errors counting correctional facility populations (Tuttle, 2021). Localities have until June 2023 to submit a PCGQR request, and should do so if there are group counts they believe were not correctly counted. Doing so will ensure an accurate population count and access to appropriate resources for college towns and the universities in them.

References

Aasa, A., Kamenjuk, P., Saluveer, E., Simbera, J., & Raun, J. (2021). Spatial interpolation of mobile positioning data for population statistics. *Journal of Location Based Services, 15*, 239-260.

Aiken, E., Bellue, S., Karlan, D., Udry, C., & Blumenstock, J. E. (2022). Machine learning and phone data can improve targeting of humanitarian aid. *Nature, 603*(7903), 864-870.

Andersen, M. S., Bento, A. I., Basu, A., Marsicano, C. R., & Simon, K. I. (2022). College openings in the United States increase mobility and COVID-19 incidence. *PLOS One, 17*(8), 1-15.

Athey, S., Blei, D., Donnelly, R., Ruiz, F., & Schmidt, T. (2018). Estimating heterogeneous consumer preferences for restaurants and travel time using mobile location data. *AEA Papers and Proceedings, 108*, 64-67.

Athey, S., Ferguson, B., Gentzkow, M., & Schmidt, T. (2021). *Proceedings of the National Academy of Sciences, 118*(46), e2026160118.

Chen, K. M., Haggag, K., Pope, D. G., & Rohla, R. (2019). Racial disparities in voting wait times: evidence from smartphone data. *The Review of Economics and Statistics*, 1-27.

Chen, M. K., & Rohla, R. (2018). The effect of partisanship and political advertising on close family ties. *Science, 360*(6392), 1020-1024.

Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F. R., Gaughan, A. E., . . . Tatem, A. J. (2014). Dynamic population mapping using mobile phone data. *Proceedings of the National Academy of Sciences, 111*, 15888-15893.

Elliot, D., Steven, M., Shakesprere, J., & Kelly, J. (2021). Simulating the 2020 Census: Miscounts and the Fairness of Outcomes. *Urban Institute*.

Ghebreyesus, T. A. (2020). WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020.

Gupta, S., Nguyen, T., Raman, S., Lee, B., Lozano-Rojas, F., Bento, A., . . . Coady, W. (2021). Tracking public and private responses to the COVID-19 epidemic: evidence from state and local government actions. *American Journal of Health Economics, 7*(4), 361-404.

Henderson, T. (2022, April 4). The Census Missed Some Folks. These Cities Want Them Counted. Pew Stateline.

Hillygus, D. S., & Lopez, J. (2020). Easy as 1, 2, 3? Challenges of the 2020 Census and Implications for Political Science. *Journal of Political Institutions and Political Economy, 1*, 289-317.

Kelchen, R., & Webber, D. A. (2018). Examining the Interstate Mobility of Recent College Graduates. *Educational Researcher, 47*(3), 213-215.

Lahanas, G., & City of East Lansing. (2021). Comment on FR Doc 2021-25283. https://www.regulations.gov/comment/USBC-2021-0025-0019.

Lai, S., Erbach-Schoenberg, E., Pezzulo, C., Ruktanonchai, N. W., Sorichetta, A., Steele, J., . . . Tatem, A. J. (2019). Exploring the use of mobile phone data for national migration statistic. *Palgrave Communications, 5*(1), 1-10.

Marsicano, C. R., Barnshaw, J., & Letukas, L. (2020). *New Directions for Institutional Research, 2020*, 7-30.

Marsicano, C. R., Felten, K., Toledo, L., & Buitendorp, M. (2021). Spring 2021 Mode of Instruction [Dataset]. The College Crisis Initiative (C2i).

Mervis, J. (2020). Will the 2020 census numbers be good enought, and how soon will we know? *Science Magazine*.

Molinaro, M., & County of Dutchess. (2021). Comment on FR Doc 2021-25283. https://www.regulations.gov/comment/USBC-2021-0025-0003.

Nguyen, T. D., Gupta, S., Andersen, M. S., Bento, A. I., Kosali, S. I., & Coady, W. (2021). Impacts of state COVID-19 reopening policy on human mobility and mixing behavior. *Southern Economic Journal, 88*(2), 458-486.

Office of the Inspector General. (2022). *Lessons Learned from the 2020 Decennial Census: Final Report No. OIG-22-030.* U.S. Department of Commerce, Office of Inspector General, Office of Audit and Evaluation. https://www.oig.doc.gov/OIGPublications/OIG-22-030.pdf.

O'Hare, W. P., Jacobsen, L. A., Mather, M., & VanOrman, A. (2020). Research Identifies New Strategies to Reduce Undercount of Young Children in U.S. 2020 Censu. *Population Reference Bureau*.

Painter, M., & Qiu, T. (2020). Political beliefs affect compliance with COVID-19 social distancing orders. *COVID Economics, 4*, 103-123.

Potok, N. A., Santos, R., Citro, C. F., Fay, R. E., Groves, R., Hogan, H., . . . Wallman, K. K. (2021). *ASA 2020 Census Quality Indicators Task Force.* American Statistical Association.

Prewitt, K. (2010). The US decennial census: Politics and political science. *Annual Review of Political Science, 13*(1), 237-254.

Reamer, A. (2020). Counting for dollars 2020: The role of the decennial census in the geographic distribution of federal funds. *George Washington Institute of Public Policy*.

Schneider, M. (2021, October 18). College towns plan to challenge results of 2020 census. Associated Press.

Skinner, A., Flannery, K., Nocka, K., Bor, J., Dean, L. T., Jay, J., . . . Scheckman, R. (2022). A database of US state policies to mitigate COVID-19 and its economic consequences. *BMC Public Health, 22*(1), 1-8.

Sullivan, T. A., & Cork, D. L. (2022). Understanding the Quality of the 2020 Census: Interim Report. Washington, D.C.: National Academies of Sciences, Engineering, and Medicine.

The United States Constitution. (1787).

Tuttle, D. (2021). 3 Takeaways (and 1 Big Headache) from the Initial 2020 Census Release. Dutchess County Planning Federation.

United States Census Bureau. (2020). Residence Criteria and Residence Situations for the 2020 Census of the United States. https://www.census.gov/content/dam/Census/programs-surveys/decennial/2020-census/2020-Census-Residence-Criteria.pdf.

United States Census Bureau. (2022). *2020 Post-Census Group Quarters Review (PCGQR)*. Retrieved from https://www.census.gov/about/policies/quality/corrections/pcgqr.html

United States Census Bureau. (2022). *Count Question Resolution Operation (CQR)*. Retrieved from https://www.census.gov/about/policies/quality/corrections/pcgqr.html

United States Census Bureau. (2023). *2020 Post-Census Group Quarters Review (PCGQR) Case Status*. Retrieved from https://www2.census.gov/programs-surveys/decennial/2020/program-management/pcgqr/pcgqr-cases-received.pdf

Woods, D., Cunningham, A., Utazi, C., Bondarenko, M., Shengjie, L., Rogers, G., . . . Tatem, A. (2022). Exploring methods for mapping seasonal population changes using mobile phone data. *Humanities and Social Sciences Communications, 9*(1), 1-17.

Yan, Y., Bayham, J., Richter, A., & Fenichel, E. P. (2021). Risk compensation and face mask mandates during the COVID-19 pandemic. *Scientific Reports, 11*(1), 1-11.

Table 1

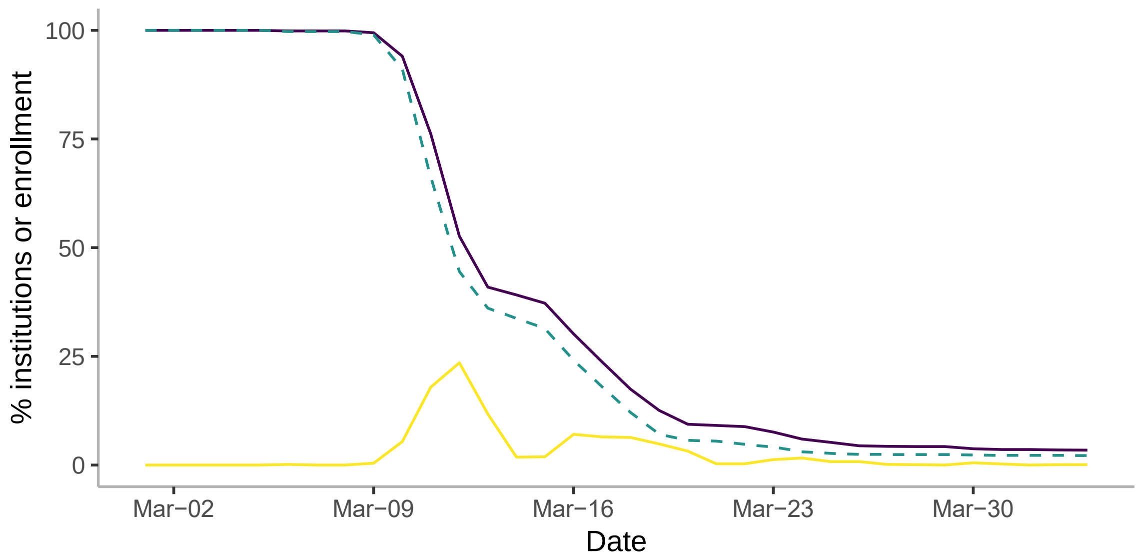
Actual and Simulated Congressional Reapportionment

State	Actual Reapportionment	Simulated Reapportionment		
		Estimate	*Half*	*Double*
California	-1	-1	-1	-1
Colorado	1	1	1	1
Florida	1	1	1	1
Illinois	-1	-1	-1	-1
Michigan	-1	-1	-1	-1
Minnesota	**0**	**-1**	**-1**	**-1**
Montana	1	1	1	1
New York	**-1**	**0**	**0**	**0**
North Carolina	1	1	1	1
Ohio	-1	-1	-1	-1
Oregon	1	1	1	1
Pennsylvania	-1	-1	-1	-1
Texas	2	2	2	2
West Virginia	-1	-1	-1	-1

Note: Actual reapportionment refers to the number of seats gained or lost in Congress based on the 2020 Census. Simulated reapportionment refers to the estimated number of seats gained or lost accounting for college student mobile device estimates. Even when the estimates are halved or doubled the number of seats gained or lost in the mobility-informed reapportionment process remains the same. Shown are any states that gained or lost seats in at least one measure of reapportionment, actual or simulated.

Figure 1

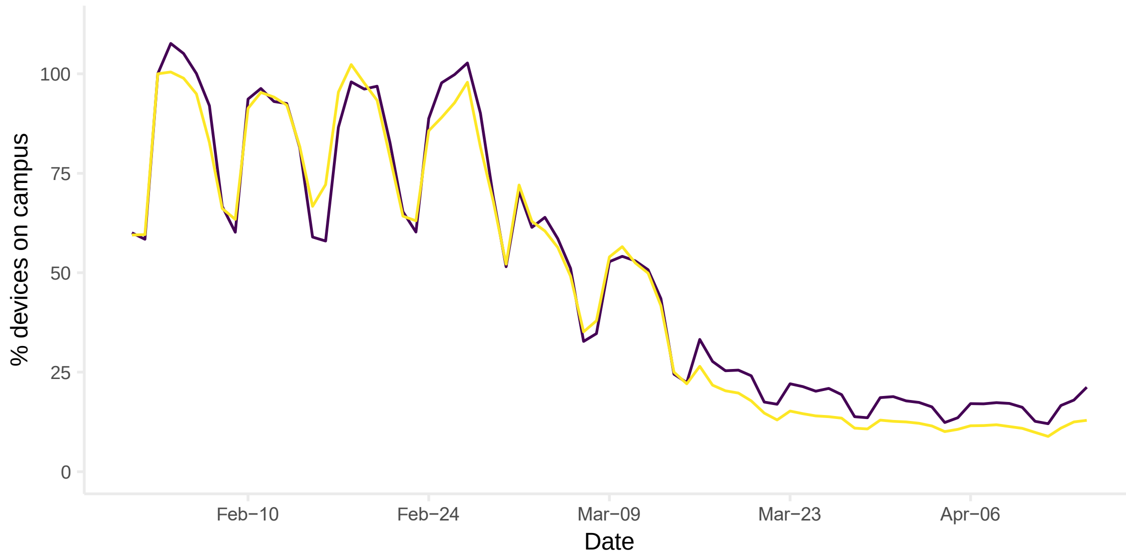
Temporary COVID-19-Related Campus Closures



Note. Temporary COVID-19-related campus closures. COVID-19 related closures increased in the second week of March, affecting over half of all institutions. There was a pronounced drop in the percent of institutions (solid purple) remaining open and percent of the total student enrollment at those institutions (dashed green) after the second week of March. Percent of the total number of institutions announcing temporary closures on a given day shown in solid yellow.

Figure 2

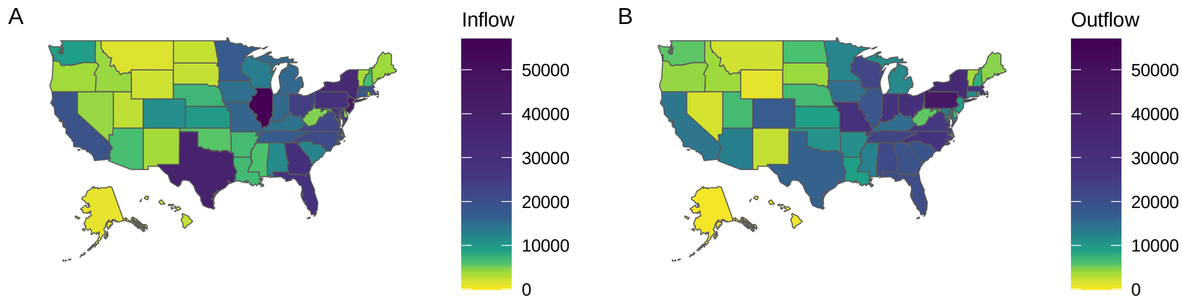
Trends in College Devices at Home, Relative to Non-College Devices



Note. There was a dramatic fall in the number of college devices visiting their home campus, relative to visits by non-college devices to their February locations for campuses with (purple) and without (yellow) a medical school. The reduction was larger for campuses without a medical school (yellow). The shaded band corresponds to the 95% confidence interval.

Figure 3

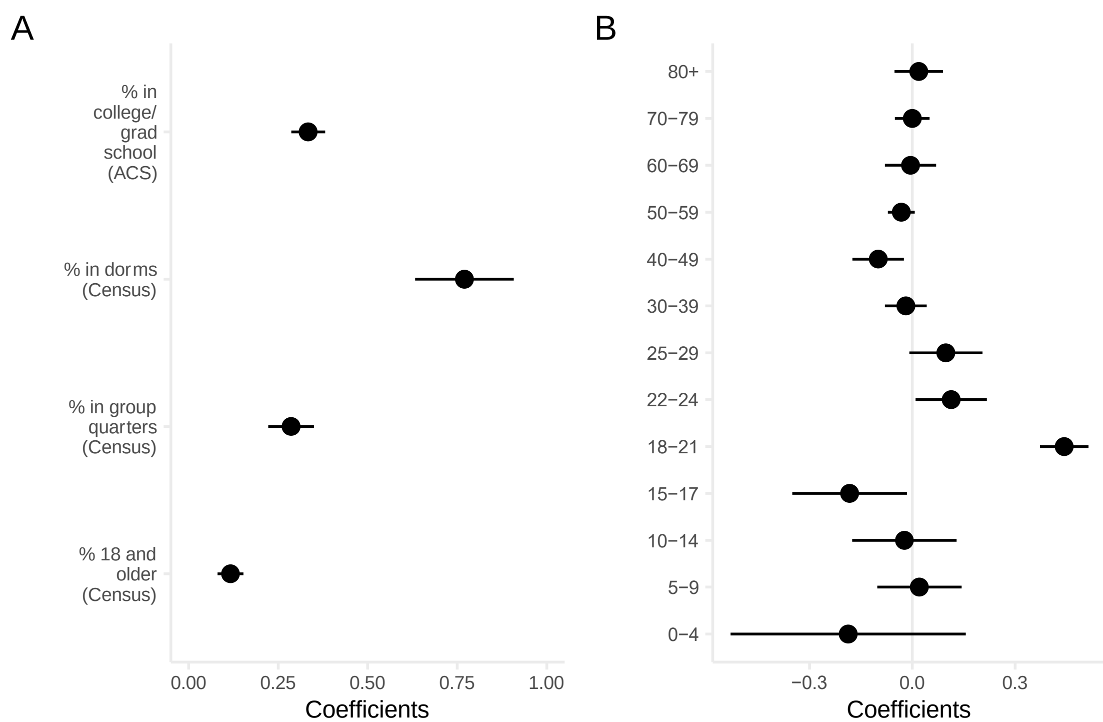
Cross-State Flows of College Devices in April of 2020



Note. Inflow (A) and outflow (B) of college devices by state between February and April 2020 demonstrate substantial heterogeneity across states in both the number of people who left the state and the number that arrive, with relatively few states having large values for both in and out flows.

Figure 4

Correlates of the Estimated Undercount in a County from the 2020 Census



Note. In separate models, the undercount was correlated with markers of college student status (**A**) and was larger in counties with a greater share of college-age students in the 2015-2019 ACS (**B**). The undercount in a county is the counterfactual population estimate, assuming college devices are at their college location, minus the baseline population estimate, which uses actual April 2020 locations. Higher values correspond to a larger undercount.

APPENDIX

Materials and Methods

Data

We collected GPS ping-level data from over 75 million opted-in cellular devices in the United States from February 1, 2020 through April 14, 2020 from Unacast. The use of these data was reviewed and approved by the Institutional Review Board at the University of North Carolina at Greensboro (IRB-FY22-200). These data provide a consistent device-identifier over time and the location and time of GPS location requests from applications that employ the Unacast SDK to collect location information. We assigned each ping to either a 2020 Census Block Group (CBG) or a college campus, using a Department of Homeland Security shapefile that identifies college campuses. For purposes of this paper, we restricted the set of college campuses in our sample to the 1,490 institutions that are located in the United States, public and private not-for-profit 4 year or above, private for-profit 4 year or above, primarily baccalaureate and above degree granting, has first-time full-time undergraduates, and offers Bachelor's, Master's, and Doctoral degrees in eight Carnegie Classifications (Doctoral Universities: Very High Research Activity, Doctoral Universities: High Research Activity, Doctoral/Professional Universities, Master's Colleges & Universities: Larger Programs, Master's Colleges & Universities: Medium Programs, Master's Colleges & Universities: Small Programs, Baccalaureate Colleges: Arts & Sciences Focus, and Baccalaureate Colleges: Diverse Fields). Institutional data were pulled from the Integrated Postsecondary Education Data System (IPEDS).

We then computed the duration between two pings (on the same day) for consecutive pings that remained in the same location – either a CBG or campus – for both pings. For each day we assigned each device to two locations, based on where the device spent the majority of its time. The first location used pings from any time during the day, while the second was restricted to pings outside of the traditional 9AM to 5PM workday.

We also computed standardized locations (all-day and outside of 9AM to 5PM) for each device for the month of February based on the most common daily location for a device in February. In the event of ties, we first used the location at which a device spent the most time across the entire month and then the location at which a device was first seen. We considered a device to be a “college” device if its primary February location was a college campus. Conversely, we considered devices with primary locations not on a college campus a “non-college” device. It is possible for a non-college device to have one, or more, days on a college campus under our assignment algorithm.

We converted cellular devices into people using the ratio of the 2020 national Census count and the total number of devices seen, on average, in April of 2020. This ratio allows us to convert device counts into population estimates and to estimate counterfactual population distributions. By construction, this ratio guarantees that the total number of people will always equal the 2020 Census population count.

We constructed two different population estimates for each state. Our first, baseline, estimate used the average number of devices in each state in April 2020 and converted the count of devices into a person count using the conversion factor described above. Our second, counterfactual, estimate reassigned college devices from their April location to their February location--specifically the state containing the college that they were assigned to.

Methods

Correlations With Device Counts

We computed the average number of devices in each county for April 1 through April 14 and compared this number to the 2020 Census population count and computed the R^2 from a log-log regression of the census count on the device count. The R^2 provides an indication of the amount of variability across counties that can be explained by variation in device counts. For college campuses we conducted a similar exercise, but used the average number of devices on a college campus in February – before the pandemic caused millions of college students to return home – and compared the average number of devices on campus to the number of beds in the dormitories as an approximation for the number of residential students on that campus.

Trends in Devices on Campuses

We estimated changes in the fractions of college and non-college devices that were in their home area over time using a two-way fixed effects Poisson model of the form:

$$E[Y_{it}|X_{it}] = \exp(\beta College_i \times \tau_t + \mu_i + \tau_t)$$

Where Y_{it} is the number of visits by devices with home location i that visited their home location on day t, $College_i$ is an indicator that a device has a college as its home location, τ_t is a vector of date indicators, with February 3 as the omitted reference group, and μ_i is a set of home location fixed effects. The coefficient vector of interest is β, which is the daily (log) difference between college and non-college devices in the fraction of devices visiting their home area. We report these results after exponentiating so that our metric is the relative percentage of devices on campus.

Defining Person-Equivalent Device Counts

In order to convert device counts to people, we, as a baseline measure, used the national ratio of the 2020 Census population estimate with the number of devices in our sample. Using this ratio, which was 28.9, we then imputed population counts for each state.

Computing the Undercount in the 2020 Census

We defined our counterfactual 2020 Census count in which college students had not returned home by counting college devices in the state of the college that they were assigned to in February of 2020, while all other devices remained at their April 2020 location. Using this counterfactual count, we defined the undercount in the 2020 Census as the counterfactual count less the actual 2020 Census count. We also computed two summary measures to decompose the change in the number of devices. We defined the "inflow" of college devices in April 2020 as the person-equivalent of the college devices in a state in April and the "outflow" as the person-equivalent of the college devices that were in the state in February of 2020. We calculated similar values at the county level assigning devices to the county containing the college.

Correlates of the Estimated Undercount in the 2020 Census

We explored the correlates of the estimated undercount using data from the 2015-2019 American Community Survey, from which we extracted: i) the share of the population that is enrolled in college or graduate school; and ii) the age distribution of ACS respondents in a county. From the 2020 Census we also identified the fractions of the population that: i) reside in a dorm; reside in any form of group quarters; and iii) were 18 or older. We then conducted county-level cross-sectional regressions of the county-level undercount on (in separate models) the ACS share enrolled in college or graduate school, the ACS age distribution of the population, the 2020 Census dorm residency, the 2020 Census group quarters residency, and the 2020 Census share 18 and older.

Supplementary Text

Validating Device Counts

Cellular Device Counts are Highly Correlated with Population Counts

The number of devices in any particular county in April of 2020 is strongly correlated with the 2020 Census count, with an R^2 in a log-log regression of 0.96 and a slope of 1.050 (95% CI: 1.040 - 1.060) on the device count (Fig. S1, panel A), which supports our contention that cellular device counts can be used to estimate populations. Fig. S1, panel B, demonstrates that there is a similar, though attenuated relationship between the average number of devices on college campuses in February, relative to the number of residential beds on campus ($\beta = 0.684, 95\%\ CI: 0.657 - 0.712$). These results suggest that cellular device counts can be used to approximate population counts.

Alternative Construction of Device-Based Population Counts

Our main estimates assume a single conversion factor for all devices in our data. Here we consider four alternative approaches to constructing device-based population counts.

Adjusting for the California Consumer Privacy Act

The California Consumer Privacy Act (CCPA) provides California residents with the right to opt out of data-sharing with entities like Unacast. Using data from SafeGraph Inc., another vendor of human mobility data that has data spanning the implementation of the CCPA, we estimate that the CCPA reduces device counts in the state by approximately 17%. To construct “CCPA-adjusted” estimates, we inflated the device count for each device that ended up in California in April of 2020 by 25% (approximately $\frac{1}{0.83}$). We then calculated a single, nationwide person to device conversion factor as the ratio of the 2020 Census count to the scaled device count.

Adjusting for Unacast's Internal Market Share Estimates

We also received internal market share data from Unacast that included estimates of the share of devices in each state that were included in the Unacast sample. These share estimates are undated and the precise method for calculating these data were not provided to us. We constructed share adjusted population estimates by first scaling the number of devices in each state in April of 2020 by the inverse of the Unacast market share and then calculating a single, nationwide conversion factor.

State-Specific Conversion Factors

A more extreme version of the CCPA and Unacast share based adjustments is to construct a single adjustment factor that captures any differences in the Unacast sample in state due to differences in app usage, state laws, or any other factors. We constructed state specific conversion factors as the ratio of the 2020 Census state population to the number of devices in the state in April of 2020. We then applied these factors to device counts based on the April location of a device.

Non-Office Time

We also used device locations outside of the normal working day to construct home locations since college students are more likely to be on campus outside of the normal working day than visitors to campus.

Across all four methods, we continue to find that county-level population estimates are highly correlated with the 2020 Census count (Fig. S2). We also find state-level population estimates that are close to the baseline estimate.

Alternative Explanations for the April Decline

It is possible that the decline in college devices in April of 2020 was part of a regular pattern for college campuses. We evaluated this possibility using “Neighborhood patterns” data from SafeGraph that counts the number of devices in the SafeGraph panel that visit a census block group in any given month and year. We defined a census block group to be a “college census block group” if it intersected with a college campus (Andersen, et al., 2022). We then estimated a two-way fixed effects Poisson regression controlling for Census block group and calendar date fixed effects and academic year by college and month by academic year by college fixed effects, which are the coefficients of interest. We plot these coefficients in Fig. S3 which demonstrates a pattern in devices visiting college CBGs in 2018-2019 that is consistent with the academic calendar--visits are lower in the summer, peak in October, reach a nadir in December before rebounding for the Spring semester. Trends in 2019-2020 were similar to 2018-2019 until March, when there was a large decline in devices visiting “college” CBGs.

Table S1

Actual and Device-Based Population Estimates

State	Census	Baseline	Adjusting for CCPA	Adjusting for Unacast Share	State-specific conversion	Non-office time
Alabama	5024279	6782367	6692203	4850500	5024279	7004930
Alaska	733391	544073	536840	964294	733391	552935
Arizona	7151502	6485292	6399078	6721232	7151502	6590547
Arkansas	3011524	4039935	3986229	2940806	3011524	4152816
California	39538223	17862272	22031019	29923691	39538223	16929026
Colorado	5773714	5573362	5499271	5926806	5773714	5571886
Connecticut	3605944	3103763	3062503	3547367	3605944	3039714
Delaware	989948	1017184	1003662	907988	989948	1002698
District of Columbia	689545	477705	471354	590100	689545	449046
Florida	21538187	25426701	25088685	22864012	21538187	25453406
Georgia	10711908	12475172	12309330	10103478	10711908	12702848
Hawaii	1455271	836051	824937	1345304	1455271	856539
Idaho	1839106	1658265	1636220	1675984	1839106	1677207
Illinois	12812508	14006838	13820635	15431867	12812508	13992356
Indiana	6785528	8519473	8406217	6854416	6785528	8539152
Iowa	3190369	4725098	4662284	3752247	3190369	4647841
Kansas	2937880	4031354	3977763	3331122	2937880	4049066
Kentucky	4505836	5344938	5273884	4328796	4505836	5367636
Louisiana	4657757	5483324	5410430	4689313	4657757	5603128
Maine	1362359	1317315	1299803	1211265	1362359	1291772
Maryland	6177224	5910716	5832141	6453918	6177224	5825595
Massachusetts	7029917	5381214	5309677	7000898	7029917	5227053
Michigan	10077331	11560285	11406605	11131819	10077331	11433518
Minnesota	5706494	6641908	6553612	6603727	5706494	6558845
Mississippi	2961279	3645708	3597243	2804052	2961279	3720669
Missouri	6154913	7724359	7621673	6382665	6154913	7862485
Montana	1084225	1013332	999861	1015765	1084225	1010157
Nebraska	1961504	2705399	2669434	2120841	1961504	2695503
Nevada	3104614	2298597	2268040	2196110	3104614	2269221
New Hampshire	1377529	1412740	1393959	1183343	1377529	1395143
New Jersey	9288994	7916684	7811442	9980974	9288994	7819610
New Mexico	2117522	1878564	1853591	1914460	2117522	1899909
New York	20201249	15069876	14869541	21183209	20201249	14716453
North Carolina	10439388	12547649	12380844	10029338	10439388	12660443
North Dakota	779094	949067	936450	811637	779094	936294
Ohio	11799448	14703309	14507847	13124895	11799448	14712672
Oklahoma	3959353	5307118	5236567	4269888	3959353	5439026
Oregon	4237256	3531040	3484099	4192439	4237256	3574152
Pennsylvania	13002700	12915682	12743984	13734752	13002700	12737097
Rhode Island	1097379	884555	872796	1050241	1097379	864009
South Carolina	5118425	6286008	6202443	4687404	5118425	6409923
South Dakota	886667	1076757	1062443	877865	886667	1065902
Tennessee	6910840	8608082	8493648	6303638	6910840	8785449
Texas	29145505	34331183	33874793	31567375	29145505	34924255
Utah	3271616	2682273	2646615	3154067	3271616	2698087
Vermont	643077	579143	571444	621272	643077	562805
Virginia	8631393	8803460	8686429	9047066	8631393	8786044
Washington	7705281	6146195	6064489	7996129	7705281	6247629

State	Census	Baseline	Adjusting for CCPA	Adjusting for Unacast Share	State-specific conversion	Non-office time
West Virginia	1793716	2008131	1981435	1659326	1793716	2000783
Wisconsin	5893718	6553099	6465984	5807230	5893718	6472908
Wyoming	576851	666667	657804	582348	576851	663092

Note: "Adjusting for CCPA" estimates increase the number of devices observed in California in April of 2020 by 25% to offset an estimated 20% reduction in devices following the implementation of the California Consumer Privacy Act in 2020. "Adjusting by Unacast market share" inflates devices seen in each state by Unacast's self-reported market share. "State-specific conversion factor" uses a separate conversion factor for each state.

Table S2

Robustness of the Percentage Undercount to Alternative Population Estimation Methods

	Baseline	Adjusting for CCPA	Adjusting for Unacast share	State-specific conversion	Non-office time
Intercept	-0.009	-0.009	-0.008	-0.008	-0.007
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
College county	0.021	0.020	0.019	0.018	0.016
	(0.001)	(0.001)	(0.0009)	(0.0009)	(0.0008)

Note: Dependent variable is the ratio of the estimated undercount to the 2020 Census count. Larger values correspond to larger relative undercounts. Coefficients from ordinary least squares regressions. Heteroscedasticity robust standard errors in round brackets. N=3143 for all models.

Table S3

Governmental Units Submitting a Request for a Secondary Review of Group Quarter Populations as of April 24, 2023

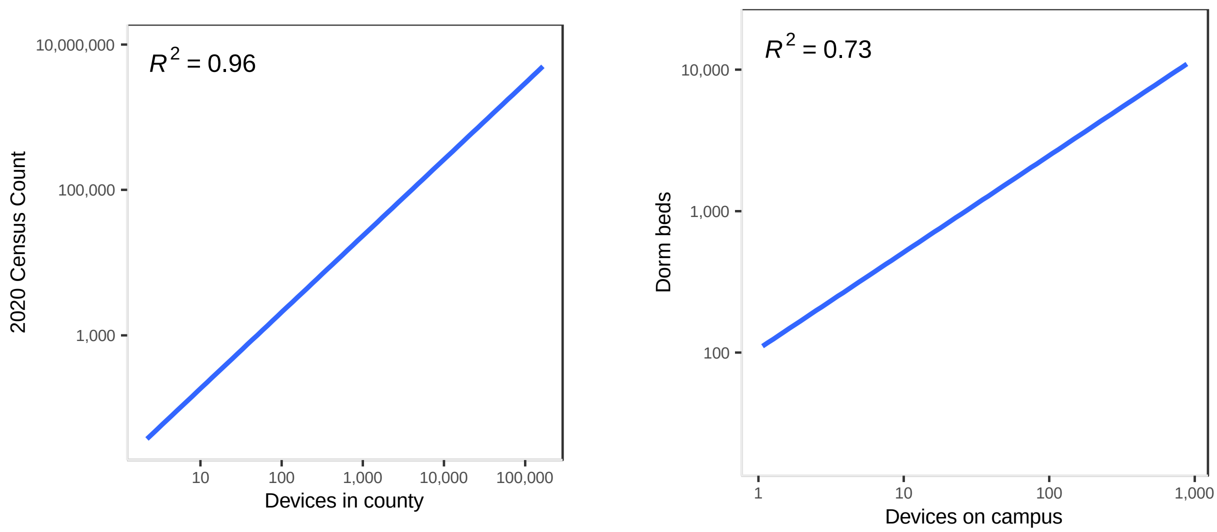
Request Date	Unit	County	State	County Undercount	Review Complete?	Colleges and Universities
Jun. 10, 2022	Jonesboro City	Clayton	GA	-1030	Yes	
Jun. 15, 2022	Waterville City	Kennebec	ME	530	Yes	Colby College, Thomas College
Jun. 16, 2022	Walnut Ridge	Lawrence	AR	187	Yes	
Jun. 22, 2022	Dutchess County	Dutchess	NY	379	Yes	Bard College, Marist College, Vassar College
Jun. 22, 2022	Town of Chester	Dodge	GA	-96	Yes	
Jun. 30, 2022	City of Crete	Saline	NE	-54	Yes	Doane University
Aug. 4, 2022	City of Yuma	Yuma	AZ	-485	Yes	Arizona Western College
Aug. 9, 2022	Town of Florence	Pinal	AZ	-1527	Yes	
Aug. 25, 2022	Chesterfield Township	Macomb	MI	-6437	Yes	
Sep. 14, 2022	City of Boston	Suffolk	MA	11840	Yes	Boston University, Cambridge College, Emerson College, Fisher College, Northeastern University, Sattler College, Simmons University, Suffolk University, University of Massachusetts - Boston
Sep. 27, 2022	City of Marina	Monterey	CA	-117	Yes	
Sep. 28, 2022	City of Granger	Dallas/Polk	IA	-1464/-2781	Yes	
Oct. 6, 2022	Village of Shiloh	St. Clair	IL	-3923	Yes	
Nov. 1, 2022	City of Goodyear	Maricopa	AZ	2685	Yes	Franklin Pierce University
Nov. 3, 2022	City of Marshall	Lyon	MN	468	Yes	Southwest Minnesota State University
Nov. 4, 2022	Detroit City	Wayne	MI	-4759	Yes	University of Detroit Mercy, Wayne State University, Sacred Heart Major Seminary
Dec. 16, 2022	Village of Romeoville	Will	IL	-5368	Yes	Lewis University
Dec. 30, 2022	City of Murray	Calloway	KY	2327	Yes	Murray State University
Jan. 27, 2023	North Bonneville City	Skamania	WA	-69	Yes	
Jan. 27, 2023	Bonney Lake City	Pierce	WA	-986	Yes	
Jan. 31, 2023	Big Rapids City	Mecosta	MI	3188	Yes	Ferris State University
Jan. 31, 2023	Luce County	Luce	MI	-29	Yes	
Feb. 1, 2023	City of Tempe	Maricopa	AZ	2685	Yes	Arizona State University
Feb. 13, 2023	Village of Bannockburn	Lake	IL	-7621	Yes	Trinity International University-Illinois

Request Date	Unit	County	State	County Undercount	Review Complete?	Colleges and Universities
Feb. 15, 2023	City of Chicopee	Hampden	MA	-508	Yes	College of Our Lady of the Elms
Feb. 28, 2023	City of Phoenix	Maricopa	AZ	2685	No	Ottawa University-Phoenix
Mar. 2, 2023	City of Springfield	Hampden	MA	-508	Yes	American International College, Springfield College-Regional Online and Continuing Education, Western New England University
Mar. 27, 2023	Racine County	Racine	WI	-1706	No	
Apr. 3, 2023	Town of Dartmouth	Bristol	MA	-1217	No	University of Massachusetts-Dartmouth
Apr. 5, 2023	City of Norfolk		VA	6445	No	Norfolk State University, Old Dominion University
Apr. 20, 2023	City of Delafield	Waukesha	WI	-5037	No	

Note: Arizona State University, Northern Arizona University, and the University of Arizona operate undergraduate and graduate programs on-site at Arizona Western College, Yuma. Franklin Pierce University owns and operates a 30-acre branch campus in Goodyear, AZ. Most of the courses are part of the institution's Doctor of Physical Therapy program. Institutions listed are public and private non-profit, non-special-focus, degree-granting universities that offer bachelor's degrees, master's degrees, and/or doctoral degrees. Data come from the US Census Bureau.

Figure S1

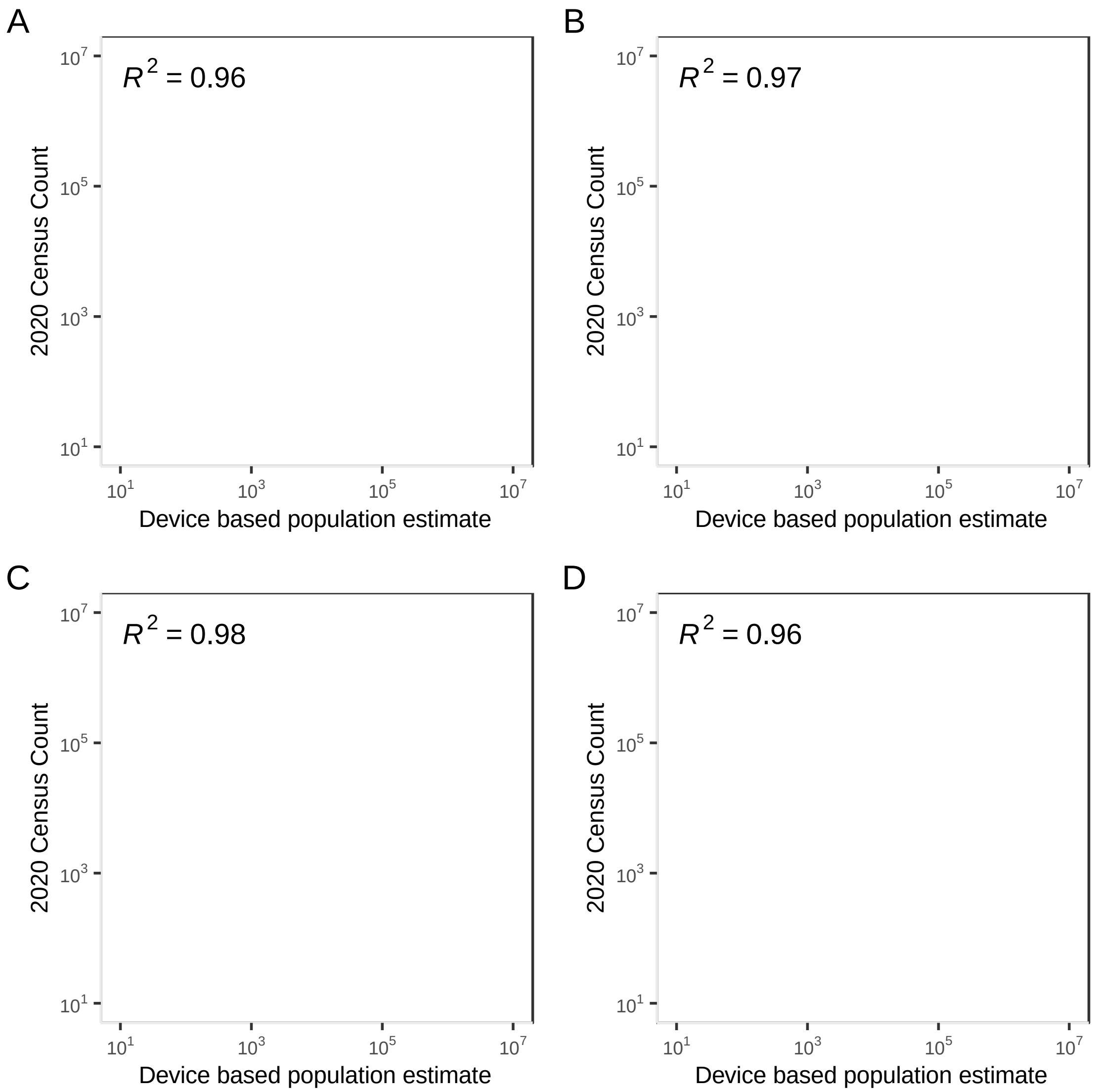
Device Counts and Population Metrics



Note. Device counts in a county in April 2020 are strongly correlated with county level population estimates from the 2020 Census (**A**). For college campuses (**B**), the number of devices on campus is highly correlated with the number of dorm beds on campus.

Figure S2

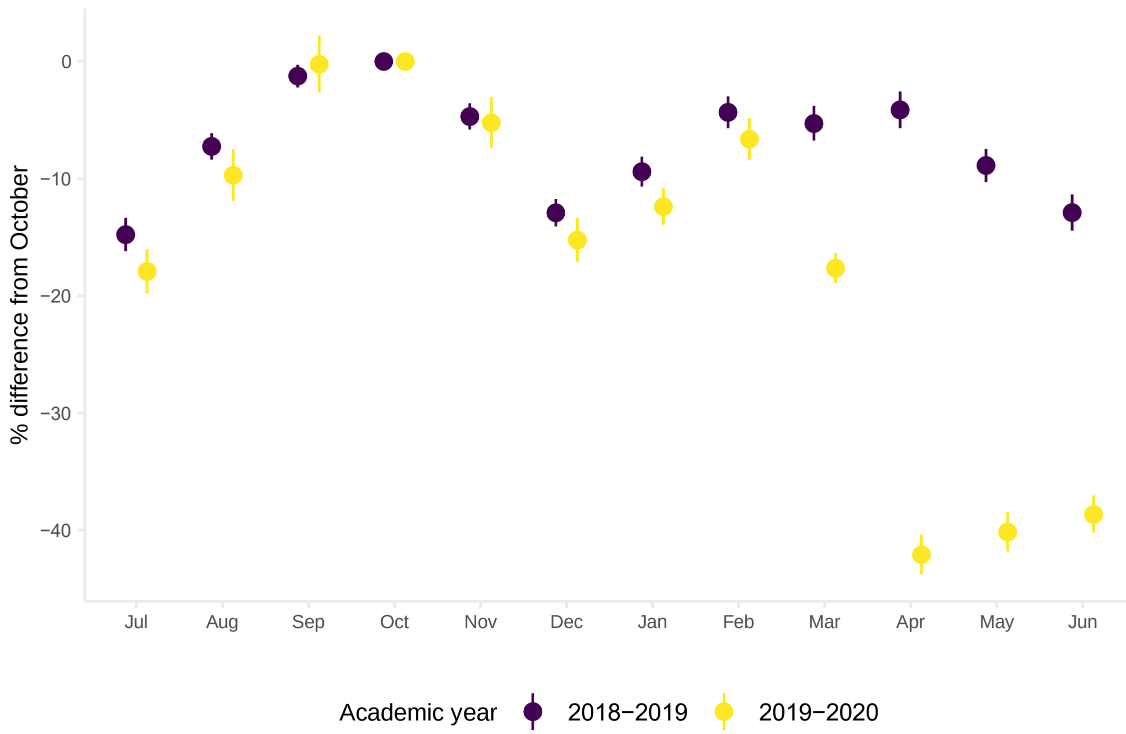
Alternative Methods to Convert Device Counts into Population



Note. A: adjusting for the CCPA; B: adjusting for Unacast's self-reported market share; C: using state-specific conversion factors; D: using non-office time to assign home locations.

Figure S3

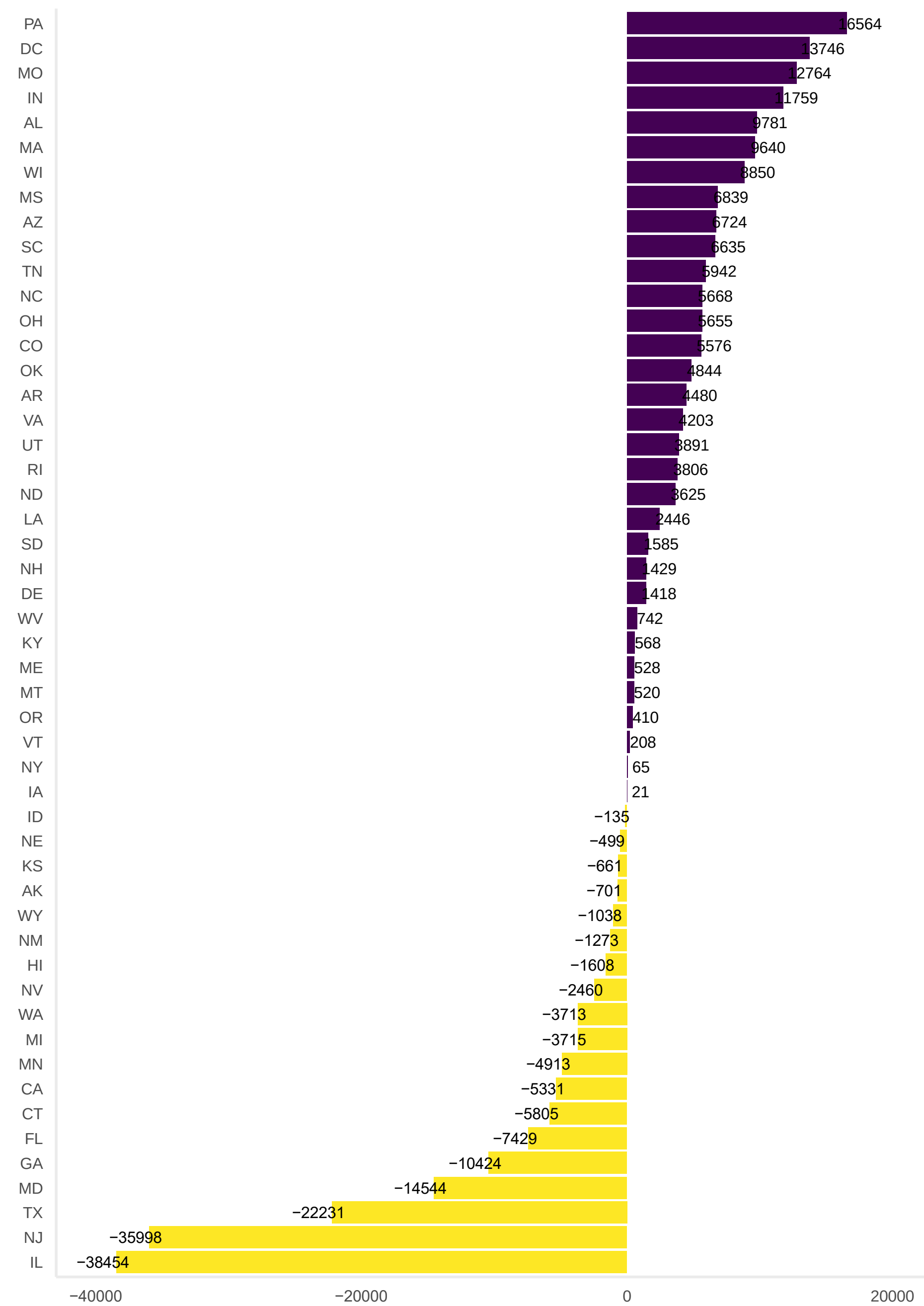
Number of Devices Visiting "College" Census Block Groups by Academic Year and Month



Note. The decline in devices visiting college census block groups in the 2019-2020 academic year was not seen in 2018-2019.

Figure S4

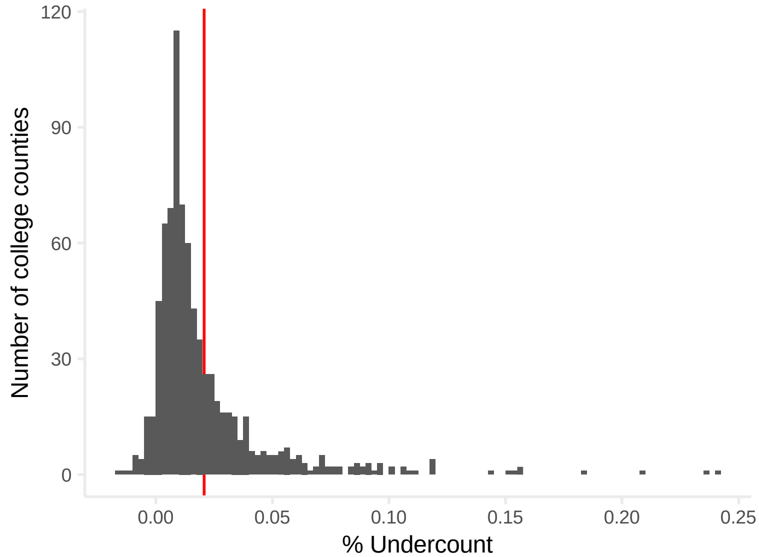
Net Change in State Population



Note. Bars are the counterfactual minus baseline population estimates for each state.

Figure S5

Distribution of Percentage of Undercounts for College Counties



Note. Results demonstrate that most college counties experienced an undercount, with 42, out of 785, college counties not having an undercount. Vertical red line is at the average undercount (2.1%).