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Addressing Nonresponse Bias in the American Community Survey During the Pandemic Using Administrative Data*

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Abstract

Due to the challenges of fielding a household survey during the COVID-19 pandemic, household nonresponse increased substantially in the American Community Survey, with evidence of increased nonresponse bias in many statistics. Specifically, higher socioeconomic status households became relatively more likely to respond during the pandemic. This likely biased estimates of many statistics, including building structure, marital status, educational attainment, Medicaid coverage, citizenship, income, and poverty. We use extensive administrative, third-party, and decennial census data to identify household and housing unit characteristics for respondent *and* nonrespondent households. We show that the pattern of survey nonresponse was unique during the pandemic period. For example, nonresponse was more strongly associated with income than in 2019. Second, we create new weights to adjust for nonresponse bias using entropy balancing, a form of empirical calibration. We evaluate the impact of our nonresponse adjustment in both 2019 and 2020 compared to the normal survey weighting. We estimate large impacts of nonresponse bias, particularly in 2020. For example, with the standard weights, real median household income increased 5.5 percent between 2019 and 2020, compared to 0.2 percent using the entropy balance weights. Overall, entropy-balance reweighting significantly reduced 2019-2020 changes in many estimates.

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1. Introduction

Starting in the spring of 2020, the COVID-19 pandemic disrupted not only the American people and economy, but also the tools used to measure them. The American Community Survey (ACS), the nation's largest household survey and the source of data guiding billions of dollars in annual spending, was forced to change its operations to protect the health and safety of U.S. Census Bureau staff and the public. At the same time, Americans also changed how they interacted with household surveys.

For example, the COVID-19 pandemic reduced response rates for the ACS. However, the ACS has never had a 100-percent response rate, and other nonsampling errors such as incomplete frame coverage have always had the potential to make its sample less representative. Adjustments have therefore always been needed to create a more nationally representative sample. In the past this has been done using statistical weights.

While survey weighting has multiple goals, one important goal is correcting for nonresponse bias. Nonresponse bias can occur when the people who agree to complete the survey (respondents) differ from sampled people who do not complete the survey (nonrespondents). Census Bureau household surveys like the ACS adjust their weights to have their age and race statistics match the estimates from the Census Bureau's Population Estimates Program (PEP). If older individuals are more likely to respond to a survey than younger individuals, for example, then this weighting adjustment will mitigate nonresponse bias with respect to age estimates. In addition to matching the PEP estimates, the ACS also contains adjustments to account for differing response rates by Census tract and building type (e.g., whether the household lives in a single-family home or an apartment complex). These weighting adjustments may have been adequate for the ACS in the 2000s and 2010s, when the response rates were above 90 percent for most years. However, the challenges of the COVID-19 pandemic appear to have increased nonresponse bias in many measures, even after the standard weighting corrections, as discussed in U.S. Census Bureau (2021). Thus, to create useful estimates for the 2020 ACS, changes to standard practices were required.

In this paper, we discuss our methodology for creating survey weights that incorporate additional data to correct for nonresponse bias in the 2020 ACS. We leverage the following administrative data for both responding and nonresponding households when constructing these new weights:[1]

1. Income, employment, financial, and household structure data from the Internal Revenue Service (IRS) 1040 and 1099 forms,
2. Program benefit data from the Social Security Administration (SSA),
3. Demographic data from the 2010 Census and the SSA,
4. Industry data for the Census Bureau's Business Register, and
5. Third-party data on home values.

To incorporate these data into the weighting procedures, we use a weighting technique called Entropy Balancing (Hainmueller, 2012), an application of empirical calibration (Deville and Särndal, 1992), which can flexibly handle high-dimensional and varied inputs to the weighting model. This method has been used successfully in prior weighting research on the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) during the pandemic, which provided the framework to extend this weighting method to the ACS (Rothbaum and Bee, 2021).

[1] We use several terms interchangeably throughout this paper to refer to these new weights: experimental weights, entropy balance weights (EBW), new weights, new survey weights, experimental entropy balance weights, and ACS experimental weights.

To examine the effects of these new survey weights, we first look at how well the reweighted ACS sample compares to benchmarks. We show that the reweighted sample more closely matches benchmark distributions, including the distributions of income and earnings in occupied housing units, race and Hispanic-origin population controls, and the distribution of educational attainment, among others. This suggests that the new weights generally reduced nonresponse bias in estimates derived from the 2020 data, compared with the standard weights.

Next, we examine how the survey estimates changed between the standard weighting methods and this new, administrative-data-based weighting method. We examine how the new weights influenced estimates in both 2020 and 2019, to evaluate the weights' performance during a period of more typical nonresponse patterns. For most characteristics identified as having anomalously large changes in estimates between 2019 and 2020 (U.S. Census Bureau, 2021), such as structure type, housing tenure, educational attainment, household income, Medicaid coverage, citizenship, and poverty, the entropy-balance weights reduced these large changes, bringing them more into line with relatively smooth historical trends.

The 2020 ACS unemployment rate did not match expectations or external benchmarks when using the production weights, and the new weights did little to improve this issue, suggesting that quality issues may still be present in the data even when using the new weights. For the sake of transparency, an online appendix offers estimates for both the standard weights and new weights in both 2019 and 2020, covering a wider variety of topics than discussed in this paper.[2] In general, we expect the new weights to improve the representativeness of ACS estimates more when we observe higher-quality proxies of these estimates in the administrative data. We also expect the new weights to improve the representativeness of ACS estimates that lack close proxies in administrative data to the extent that these estimates are correlated (in the appropriate direction) with the administrative data that we do observe. For example, we lack administrative data on educational attainment, but the high correlation between education and income implies that we are likely able to correct for much of the bias in education statistics by reweighting to make respondents' administrative income more representative of the overall sample. It is possible, as with any reweighting, that the new weights may worsen the representativeness of ACS estimates if an unobservable characteristic strongly predicts response after conditioning on the observable characteristics in the data that we use to reweight.

In summary, we provide suggestive evidence that these new weights have significantly improved the utility of the 2020 ACS data, and that they will allow the ACS to remain a useful source for studying the U.S. population during this eventful period. Nevertheless, data quality issues surely remain for some topics. Additionally, this experimental methodology has not been as thoroughly investigated and tested as the standard weighting practices applied at the Census Bureau. More research is needed into the properties of novel methods that incorporate administrative data into weighting algorithms for Census Bureau surveys.

[2] For the full list of appendix tables, tables that begin with "WXK," that accompany this report, go to https://www.census.gov/library/working-papers/2021/acs/2021_Rothbaum_01.xlsx. These tables show the standard weights and entropy balance weights for both 2019 and 2020, and their comparisons. For the full set of 2020 ACS 1-year experimental tables that begin with "XK," go to 2020 ACS 1-Year Experimental Data Tables (census.gov). These tables are similar in format to the 2019 1-year supplemental estimates published on data.census.gov with a Table ID that beings with "K".

2. ACS Data Collection in 2020

2.1 Standard ACS Data Collection Methods for Housing Units

The ACS samples approximately 3.5 million addresses each year, divided into twelve monthly sample panels. Data collection for these monthly panels occurs continuously throughout the year. Households can respond using various modes.[3,4]

Each month, the Census Bureau's National Processing Center (NPC) mails a new group of sampled addresses their first invitation to complete the ACS.[5] This initial invitation includes a link to complete the ACS online. Households that do not complete the internet questionnaire receive another mailing from NPC containing a paper questionnaire about three weeks after their initial invitation. Households can also complete the questionnaire over the telephone using Telephone Questionnaire Assistance (TQA). Most often, responses come from one of these self-response modes; in 2018, 65.7 percent of responding households used one of these three modes.[6] Households can receive up to five invitations and reminders in the mail to complete the ACS from NPC, coming within a two-month span.

In the third month after receiving their initial invitation, remaining nonrespondents are subsampled for Computer-Assisted Personal Interview (CAPI). Interviewers attempt to conduct phone or personal interviews with the selected remaining nonrespondents and encourage self-response among those reluctant to participate in a personal interview. When interviewers attempt but do not contact a household member at an address, they can leave letters with instructions for the household to respond via the internet. The incidence of self-response during the CAPI data collection month among the CAPI subsample has risen over time (Baumgardner, 2018).

Consider the example of the February panel in a typical year to summarize and concretize standard ACS data collection methods. February panel members receive their initial invitation from NPC to complete the ACS online in February. They receive up to four more mailings from NPC throughout February and March, one of which includes a paper questionnaire. In April, selected remaining nonrespondents are contacted by a CAPI interviewer to complete a personal interview. Interviewers encourage self-response in April among remaining nonrespondents who cannot be contacted or who are reluctant to complete an in-person interview.

2.2 Coronavirus Disruptions

The COVID-19 pandemic affected all 2020 ACS panels, although the extent of the impact varied by panel. Beginning in March 2020, mandatory stay-at-home orders and elevated community transmission forced numerous important changes to normal ACS data collection methods.[7] These changes affected the likelihood of self-response as well as the likelihood of response to an in-person interview.

Major operations conducted for the ACS at NPC were halted. NPC had sent out initial invitations to complete the ACS online, as well as one reminder mailing to all March panel households, and it was in

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[3] Refer to U.S. Census Bureau (2021) for a more detailed description of normal ACS data collection operations.

[4] The ACS also collects data from group quarters facilities, such as correctional facilities for adults, nursing homes, college/university student housing, military quarters, and group homes. Due to the more limited availability of administrative data for group quarters residents, we focus on the housing unit sample in this paper. For more information on the impact of the pandemic on data collection in group quarters refer to U.S. Census Bureau (2021).

[5] Not all sampled addresses receive this initial invitation. For example, households in remote areas of Alaska and addresses that are deemed unmailable are only sampled via CAPI.

[6] Retrieved from https://www.census.gov/library/visualizations/interactive/acs-collection.html, accessed 9/30/21.

[7] Refer to U.S. Census Bureau (2021) for a detailed description of disruptions to ACS data collection operations in 2020.

the process of mailing out the paper questionnaire packages for the March panel. NPC had enough time to label and mail paper questionnaire packages for only about 26 percent of the workload before operations were halted. The remaining mailings for the March panel and all mailings for the April, May, and June panels were cancelled.

Staff started returning to NPC gradually in early June. NPC resumed mailing initial invitations to complete the ACS online for all July panel members. However, social distancing rules and the very limited number of staff returning resulted in several important changes to the usual sequence of ACS mailings. First, NPC could only mail paper questionnaire packages to 67 percent, 84 percent, and 82 percent of the workload for the July, August, and September panels, respectively. There were sufficient resources to mail reminders to complete the ACS online to households that were in the paper questionnaire workload but did not receive paper questionnaire packages. Second, NPC did not resume the second (a reminder letter) or fourth (a reminder postcard) mailings for the remainder of 2020. The fifth mailing, a final reminder letter, was resumed beginning with the October panel.

The telephone centers were also limited in operations, as only managers reported to the centers for work. Respondents calling the TQA number were told to leave messages. Managers returned those calls when possible. The TQA operation resumed in July.

The CAPI operation was restricted to telephone-only interviewing on March 20, 2020, when interviewers would usually attempt to complete in-person interviews with selected remaining nonrespondents from the January panel. CAPI interviewing remained telephone-only through April, May, and June. For households sampled in April, May, and June, interviewers continued waiting until the third month to conduct interviews, following the pre-pandemic timeline. While the usual CAPI workload is between 64,000 and 68,000 cases, 80,000 CAPI cases were allowed for May and June to increase response.

During this time, interviewers used two main tools to contact households that were selected for CAPI interviews. First, they used an existing database of phone numbers purchased from third-party vendors to look up phone numbers associated with sampled addresses. However, this database did not have valid phone numbers for a significant portion of these households. In months when interviewing was restricted to telephone only, interviewers were unable to contact about 40 percent of the CAPI workload, compared with less than 0.1 percent of the CAPI workload averaged across all 2019 panel months. Second, starting in May, the Census Bureau's regional offices began mailing a "Please Call Me" letter to all addresses selected for CAPI. This letter encouraged residents to call the interviewer or to complete the interview online.

In-person CAPI interviews resumed in July in some geographic areas, covering about 28 percent of the overall CAPI workload. In August, in-person interviews were allowed for about 36 percent of the workload, and by September, all areas were allowing in-person interviews. When COVID-19 cases increased again in the fall and winter, some geographic areas returned to telephone-only CAPI interviewing, covering 5 percent of the workload in November (with 95 percent being in person) and 13 percent of the workload in December (with 87 percent being in person). The "Please Call Me" letter was used through October, even after in-person interviewing had resumed. In November, NPC began assembling and mailing a similar letter to all CAPI cases to encourage response via Internet and cooperation with field interviewers.

To summarize, the COVID-19 pandemic had diverse and complex impacts on response to the ACS. Closures and restrictions at the NPC and telephone centers affected the likelihood of self-response.

Suspension of in-person interviews affected the likelihood of response among households that did not respond on their own. The Census Bureau issued a staggered, multi-pronged response to these challenges, so that each of the twelve panels faced a different set of conditions affecting the likelihood of response.

The April, May, and June panels were particularly affected because all five mailings from NPC were cancelled. Despite this disruption, internet response was available for these cases. However, for a sample unit in these three panels to be aware that it was invited to complete the ACS, it had to be selected for CAPI and successfully contacted by the interviewer. The interviewer could then instruct that household how to respond online. CAPI interviews for the April panel occurred in June, when interviewing was still conducted only over the telephone. Consequently, interviewers could only contact April panel members if their telephone number was listed in the lookup database or if the household reacted to the “Please Call Me” letter. CAPI interviews for the May and June panels occurred in July and August, respectively, so interviewers in some geographic areas also had the option of an in-person visit to contact sampled units in these panels.

As expected, these disruptions to normal ACS data collection yielded lower response rates (U.S. Census Bureau, 2021). The April through June 2020 panels all experienced response rates via internet, mail, and TQA between 6 and 7 percent, compared with 63.6 percent on average across 2019 panels. While internet, mail, and TQA response rates rose steadily beginning with the July panel as NPC ramped up to the normal mailing schedule, they only reached 57.6 percent by the December 2020 panel.

CAPI response rates fell to 45.6 percent in April, compared with over 80 percent on average across months in 2019. Such a large decline in CAPI response rates under normal data collection operations would be enough to raise data quality concerns, but these concerns were even more heightened in 2020 because CAPI was the primary response option for three panel months due to the NPC shutdown. While CAPI response rates rose steadily beginning in July as in-person interviews ramped up to normal levels, CAPI response rates failed to reach 2019 levels before in-person interviews were restricted again due to rising community transmission.

The ACS had a much smaller sample of respondents for the April through June panels for two reasons. First, sample members who were not selected for CAPI interviews would have responded on their own, but they never received notice that they were invited to complete the ACS. Since these households were not eligible for CAPI interview, their nonresponse is not reflected in the ACS noninterview rate. The disruptions to NPC mailings reduced the overall sample size from the planned 3.54 million to 2.87 million, a reduction of 18.9 percent (U.S. Census Bureau, 2021). Second, sample members who were selected for CAPI interviews had lower response rates compared to 2019 panel members. The influence of the lower CAPI response can be seen in the noninterview rate, which was 51.5 percent for April panel households. Although in-person interviewing had resumed in some geographic areas for May and June panel members, the noninterview rate for these panels was still 44.7 percent and 43.3 percent, respectively. By contrast, the ACS noninterview rate averaged across 2019 panels was only 12.2 percent.[8] The combination of the reduced sample size and the reduced effectiveness of data collection reduced the total interviews from 2.06 million in 2019 to 1.41 million in 2020, a reduction of 31.6 percent.

[8] The noninterview rate includes both CAPI housing units that were in scope for an interview and CAPI housing units that were out of scope for an interview. The proportion of all housing units that were ultimately selected for CAPI and out of scope for an interview was 4.4 percent in the April 2020 panel, 4.7 percent in the May 2020 panel, 4.7 percent in the June 2020 panel, and 4.1 percent averaged across all 2019 panel months.

2.3 Implications for Estimates

If response to the ACS in 2020 was completely at random, the disruptions to data collection and the resulting decrease in response rates would still yield unbiased estimates, albeit with larger margins of error. If response was instead correlated with household and individual characteristics, the disruptions to data collection and the resulting decrease in response rates could yield biased estimates of those characteristics.

A variety of evidence suggests that nonrandom nonresponse did indeed result in biased estimates, even with the survey weights (discussed in Section 4), which are designed to address differential response by building type, race, Hispanic origin, age, and gender. Compelling evidence comes from substantial changes observed among estimates for four characteristics that should not change much from year to year and two characteristics for which there is a timely and reliable external benchmark. This evidence is described in detail in a separate report (U.S. Census Bureau, 2021); we summarize it here.

The fact that substantial differences were observed for four characteristics that should not change much led subject matter analysts to question the accuracy of the 2020 ACS 1-year estimates. For a fifth characteristic, one that has a timely and reliable external benchmark (Medicaid enrollment), the ACS 1-year estimates moved in the opposite direction compared with the external benchmark between 2019 and 2020. For a sixth characteristic, the second with a timely and reliable external benchmark, the ACS 1-year estimates moved in the same direction as the external benchmark (the number of people with a college degree), but the magnitude of the change was suspiciously large. These unexpected estimates informed the decision to not release the standard set of 1-year data, because they did not meet the Census Bureau's quality standards.

First, the ACS measures the structure type of the building in which housing units are located (e.g., mobile homes, single-family detached homes, 50+ unit apartment buildings, etc.). These measures typically change incrementally over time, as housing units are added to or removed from the residential housing stock through new construction, demolition, conversion to non-residential uses, and other processes. The year-over-year changes in building structure type between 2016 and 2019 illustrate this incremental change, with the estimated share of each structure type changing by no more than 0.4 percentage points between any two years. In contrast, the estimates in the 2020 ACS imply an increase of 1.8 percentage points in the share of single-family units. This shift would imply an increase of more than 3.2 million single-family homes during a period when the total number of housing units (of all types) increased by only 1.1 million units in the ACS sample. Offsetting this increase, the 2020 ACS estimates also imply year-over-year losses of 570,000 mobile homes and 1.6 million units in buildings with two or more apartments between 2019 and 2020.[9]

Second, the 2020 ACS data show a marked increase in the proportion of adults who were married and a marked decrease for those who were never married. The distribution of marital status was fairly stable over the prior four years of ACS 1-year data, so the shift in 2020 data is notable. For example, the percentage of those 15 and over who were married shifted no more than 0.3 percentage points in any year from 2016 through 2019, but it changed by 1.4 percentage points between 2019 and 2020. Conversely, the never-married share consistently increased between 2016 and 2019 by less than 0.2 percentage points per year, but it declined by 0.3 percentage points between 2019 and 2020. There is little reason to believe that these results reflected an actual change in the marital status of U.S. residents.

[9] The category of mobile homes includes mobile homes, boats, RVs, vans, etc.

A third characteristic exhibiting unexpectedly large changes in the 2020 ACS data is the proportion of adults in the U.S. with a bachelor's degree or higher. The proportion of adults with a bachelor's degree or higher has been slowly increasing over time; it had not increased by more than 0.7 percentage points in any year between 2016 and 2019. However, 2020 1-year ACS data show a large increase from 2019 to 2020, with the number of people aged 25 and over with a bachelor's degree or higher growing by 2.3 percentage points. Other data sources, such as administrative records from the National Student Clearinghouse, do not reflect an especially large increase in the number of first-time graduates earning a bachelor's degree in the 2019 to 2020 academic year (Huie et al., 2021).

Fourth, the 2020 ACS data show a notable decrease in the noncitizen population, although this characteristic tends not to change much from year to year. The noncitizen population remained between 21.7 and 22.6 million during the years 2016 to 2019, but the 2020 ACS estimates the population at 20.1 million, declining 1.6 million from 2019. Some of this decline may be true demographic change. However, much of the observed decline is likely due to nonresponse bias, since the foreign-born—and noncitizens in particular—disproportionately respond to the ACS via in-person interview methods like CAPI that were curtailed in 2020.

Fifth, the ACS asks respondents to report whether they have any of six types of health insurance coverage at the time of the interview, including private insurance, Medicare, and Medicaid. From 2014 to 2019, ACS estimates of the number of people covered by Medicaid at the time of interview generally tracked well against the timely and reliable administrative data from the Centers for Medicare and Medicaid Studies (CMS). However, the 2020 ACS estimates a 2.4-million-person decline in Medicaid coverage, while administrative data from the CMS shows a 9.8-million-person increase in Medicaid coverage from February 2020 to January 2021.

Sixth, the ACS asks respondents to report their income over the last twelve months. Measuring median household income during an unprecedented period of economic uncertainty would have been challenging without having to consider the impacts of collecting data during a global pandemic that shut down businesses, saw vast unemployment, and mandated stay-at-home orders. As documented in the CPS ASEC context (Rothbaum and Bee, 2021), the same disruptions that changed underlying economic conditions *also* changed the tools used to measure those conditions. While the ACS traditionally has shown lower median household incomes than the CPS ASEC for myriad reasons, the two measures traditionally have not diverged in such magnitude as the observed difference between the 2020 ACS and the average of the two medians from the 2020 and 2021 CPS ASEC.[10] The median household income in the 2020 ACS is $1,454 higher than the average of the 2020 and 2021 CPS ASEC medians, while the ACS had a lower median in each of the prior four years. Not only is the difference between the ACS and the CPS ASEC concerning, but the difference between the 2019 and 2020 ACS is also notable. Median

[10] One-year ACS estimates are compared to two-year average CPS ASEC estimates to account for the differences in the reference periods for the two surveys. The CPS ASEC asks respondents to report on their income in the previous calendar year while the ACS asks about income in the prior 12 months. Since the ACS is a continuous survey administered throughout the year, some respondents to the 2020 ACS (those who fill out the survey in January 2020) are reporting income received between January 2019 and December 2019 while other respondents (those who fill out the survey in December 2020) are reporting income received between December 2019 and November 2020. Therefore, 2020 ACS estimates can be thought of as roughly centered around the end of January 2020. The estimates from the 2020 and 2021 CPS ASEC are for income received in 2019 and 2020, respectively, so their average is roughly centered around the beginning of January 2020. Thus, the 2-year average of the CPS estimates is about the best one can do to get timing of income reports comparable to those used by the 1-year ACS estimates.

household income was estimated to have increased 5.5 percent, larger than any change in the last five years.

3. Linked Administrative and Census Data

To further explore nonresponse bias in the 2020 ACS, as well as to correct for any nonresponse bias through weighting, we match various administrative records data sets to ACS sampled addresses. This process enables us to observe demographic, economic, and housing characteristics of sampled households, regardless of whether they ultimately responded to the survey. We link at the address level rather than the person level because the person-level linking identifier used at the U.S. Census Bureau (PIK) cannot be directly assigned to people in nonrespondent households. Details on these linkages are described in the rest of this section.

Our primary administrative data consist of tax data from the Internal Revenue Service (IRS). First, we use IRS Form 1040 individual income returns. The 1040 returns include income from the prior year as well as the identities of the first four children or family members claimed as dependents. Next, we use IRS information returns, which include W-2s from employers, 1099 forms such as the Form 1099-INT, and Form 1098. These forms give us additional information on a variety of sources of income, as well as broader economic and financial activity.[11] Receipt of a 1098 from a mortgage lender indicates whether the household has a mortgage, and thus is a proxy for home ownership. Filing status from a 1040 return also gives us a proxy for marital status. Our matching and data construction procedures resemble those of Eggleston and Westra (2020), which examines administrative data-based weights for the Survey of Income and Program Participation (SIPP). Our work for the ACS uses some additional data sets, such as program benefit data from the Social Security Administration (SSA).

To match survey and administrative records at the address level, we utilize the linking identifier in the Master Address File (MAF), which is the Census Bureau's frame file of all known living quarters and certain nonresidential addresses in the United States. The MAF is the sampling frame for the ACS, so all ACS observations have this linking identifier, called the MAFID. The IRS data are linked to the MAF using a probabilistic linking algorithm. Looking at 1040 data, Bee, Gathright, and Meyer (2015) find that about 90 percent of Form 1040 records matched to a MAFID. Because this match rate is less than 100 percent, there could be concerns that 1040s linked to the MAF may be different from unlinked 1040s. Bee, Gathright, and Meyer (2015) examine this as well and find that unmatched tax records tend to be in the extreme upper and lower ends of the income distribution. For our analyses, this finding implies that there are two possible reasons for why a household does not match to IRS data. It could be that this household did not file their taxes or receive any other tax form (among those provided to the Census Bureau) from an employer or other third party. However, it could also be the case that they did have one of these tax forms, but had certain characteristics resulting in their tax form failing to match to the MAF. While this non-linkage makes the reweighting less efficient, it remains consistent if the relationship of non-linkage to the data is independent of survey response.

3.1 Construction of Household Roster

After linking several administrative datasets to the ACS by address (MAFID), our second step is to use the administrative data to construct a household roster for each address that we then use as a basis for matching additional person-level datasets. Our primary sources for constructing a household roster are the IRS 1040 returns and the IRS information returns (e.g., Forms 1098, 1099, and W-2). Importantly, the

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[11] While these administrative records cover almost all housing units in the 50 states and the District of Columbia, there are some important gaps in their coverage. Some households do not file taxes or do not receive any information returns. We observe nothing about these households if they do not respond to the ACS. Similarly, the IRS does not administer taxes in Puerto Rico. Finally, our administrative records do not properly cover many types of group quarters, such as prisons. Consequently, we do not attempt to construct entropy balanced weights for housing units in Puerto Rico or for group-quarters addresses.

dependent information on the 1040s gives us information about children in the household. Using the information returns in addition to the 1040s is useful for picking up individuals who do not have any filing requirements. For example, retired individuals who only receive Old-Age, Survivors, and Disability Insurance (OASDI) benefits typically do not have any taxable income. These individuals then might not file an IRS 1040 tax return, but they would receive an SSA-1099, so using the information returns helps us add them to household rosters.

However, some individuals in the United States do not appear in any IRS data available to the Census Bureau. To capture some of these individuals, we utilize two additional sources when constructing the household rosters. First, we use location information from Census Bureau's Master Address File Auxiliary Reference File (MAFARF). The MAFARF contains residency information from IRS data and other administrative data sources, such as data sets from the United States Department of Housing and Urban Development (HUD). Thus, the MAFARF picks up some additional people who do not have any taxable income. Second, we use data on Supplemental Security Income (SSI) recipients from SSA's Supplemental Security Record (SSR). Since SSI is not taxable, individuals who only receive SSI income would not appear in IRS data. In addition, the SSR is not used in construction of the MAFARF. Thus, the MAFARF and SSR allow us to pick up additional people who do not appear in IRS data.

Nevertheless, the administrative record-based household roster we construct may still miss some individuals who would be residents of the address at the time of the ACS interview. However, our reweighting exercise does not require us to exactly replicate the household roster that appears (or, for nonrespondents, would appear) in the ACS. Instead, we merely need to construct a *proxy* of who resides in each household. If this proxy is comparable between respondent and nonrespondent ACS households, then the reweighting is consistent. The more closely correlated these proxies are to dimensions of the data that are correlated with response, the more efficient the weighting becomes. For example, consider the children of divorced parents. A custody agreement may result in a difference between which parent claims the child on the 1040 in a year and where the child is deemed to reside in accordance with ACS residency rules. However, as long as these discrepancies are similar between respondent and nonrespondent households, the reweighting remains consistent. To the extent that these discrepancies are relatively rare, they only result in small reductions in how well our administrative data variables are correlated with the ACS survey data, and thus the efficiency of the reweighting process.

3.2 Additional Data Linkage

Given the household roster, we link additional datasets to infer more information about these households. We use demographic data from the SSA's Numident file and the 2010 Decennial Census. Both the Numident and 2010 Census data contain information on an individual's age and race. If race data are available from both sources for a person, we use decennial race. The 2010 Census gives us information on Hispanic origin, while the Numident data contain information on citizenship and foreign-born status.

Both these datasets are linked to the IRS-based household rosters at the individual level using the Census Bureau's Person Identification Validation System (PVS), as described by Wagner and Layne (2014). This procedure matches both survey data and administrative data to a master reference file. Individuals who are matched are given an identifier called a Protected Identification Key (PIK), which acts as an anonymized Social Security number that can be used to link administrative datasets and surveys. For the 2010 Census, about 90 percent of individuals were assigned a PIK (Wagner and Layne, 2014).[12] Bond et

[12] The 2010 Census is also linked to the MAF. Because many people have changed their residential location since 2010, however, we link decennial data at the person level instead, to make sure we are capturing the characteristics of the current household.

al. (2014) argue that inability to assign a reliable PIK is nonrandom. They use 2009 ACS data to document that young children, minorities, immigrants, recent movers, low-income individuals, and non-employed individuals are less likely to receive a PIK. Our reweighting algorithm accounts for this nonrandom ability to observe characteristics in administrative records linked to the household roster by PIK.

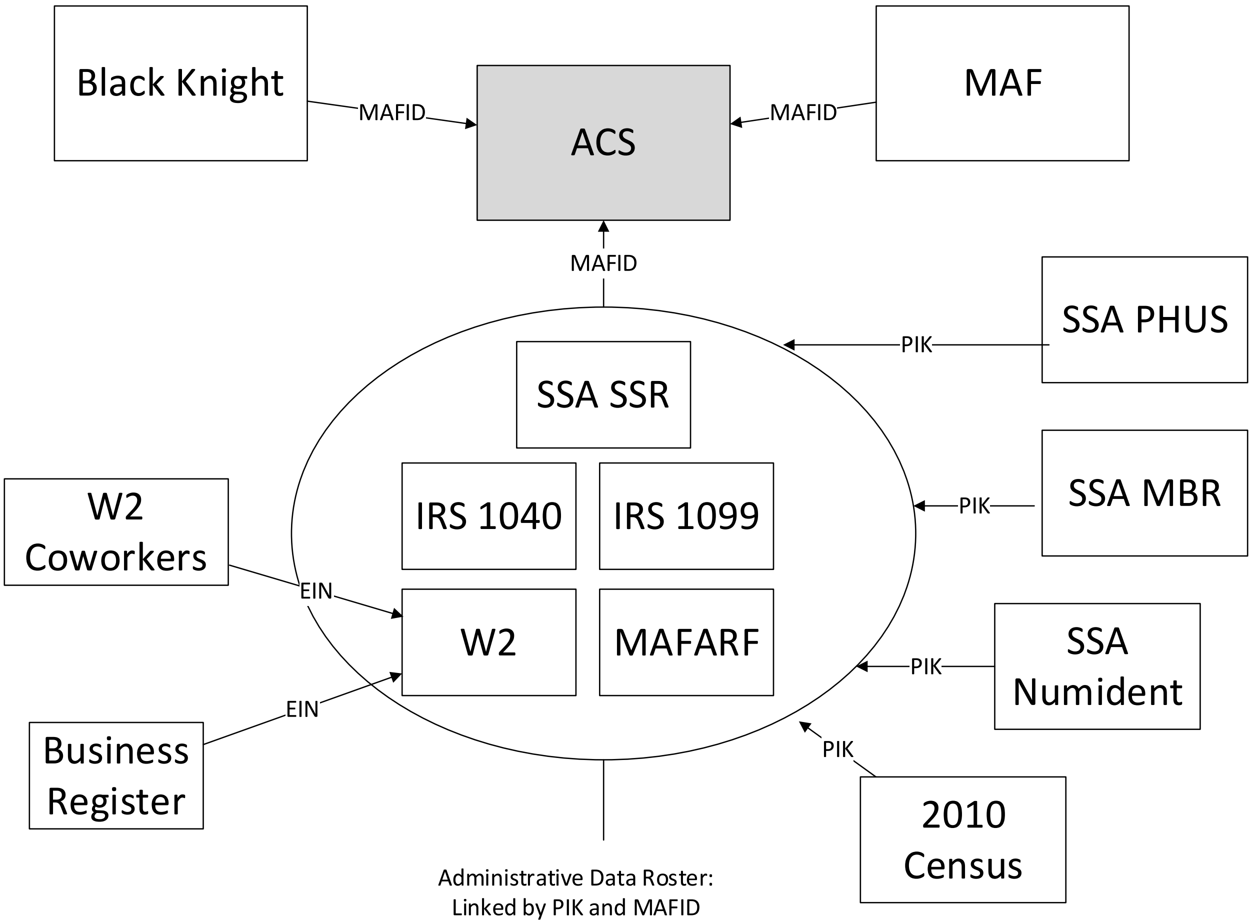
Once the Numident and 2010 Census data are matched at the individual level, the data are then aggregated to the household level to create address-level measures for comparing respondent and nonrespondent households. For example, our measure of the presence of a household member over age 60 comes from taking the list of people given on the tax forms matched to this address, and then matching these people to the Numident file to get the year of birth for all household members. Additionally, we also match OASDI program benefit data for SSA's Master Beneficiary Record (MBR) and the Payment History Update System (PHUS) at the person level using PIK.

For obtaining information about employer characteristics, we use the Employer Identification Numbers (EIN) on the W-2s matched to the households and match additional data at the EIN level. First, we leverage the W-2s of a household member's coworkers to obtain a proxy of how many people work at their employer. Second, we use the Census Bureau's Business Register to obtain information on the industry each household member works in. Given that the employment of people in the hospitality and food service industry was particularly affected by COVID-19 restrictions, this industry information may be particularly valuable for economic outcomes in 2020. Note that this linkage by EIN is imperfect for many businesses, as EIN is neither a firm nor an establishment identifier for multi-establishment firms. In other words, the number of people who share the same EIN may not always equal the number of people that work at a person's place of business. However, since our goal is to construct proxies for employer characteristics rather than to construct precise establishment-level statistics, and we do not expect the validity of these proxies to vary by survey response, we believe the EIN linkage is sufficient as an input for our weighting algorithm.

Finally, we link commercial housing data from Black Knight, a third-party vendor, as well as structure-type information from the MAF. From the Black Knight data, we use information on the home's assessed value as well as whether it is owner-occupied. The home's value, as well as whether the residence is a single-family home or in a multi-unit structure, provides additional information on the socioeconomic status of households, particularly for households that we are unable to match to any other administrative data.

To help further explain the matching process, Figure 1 gives a graphical representation of how the data are linked.

Figure 1: Matching Diagram



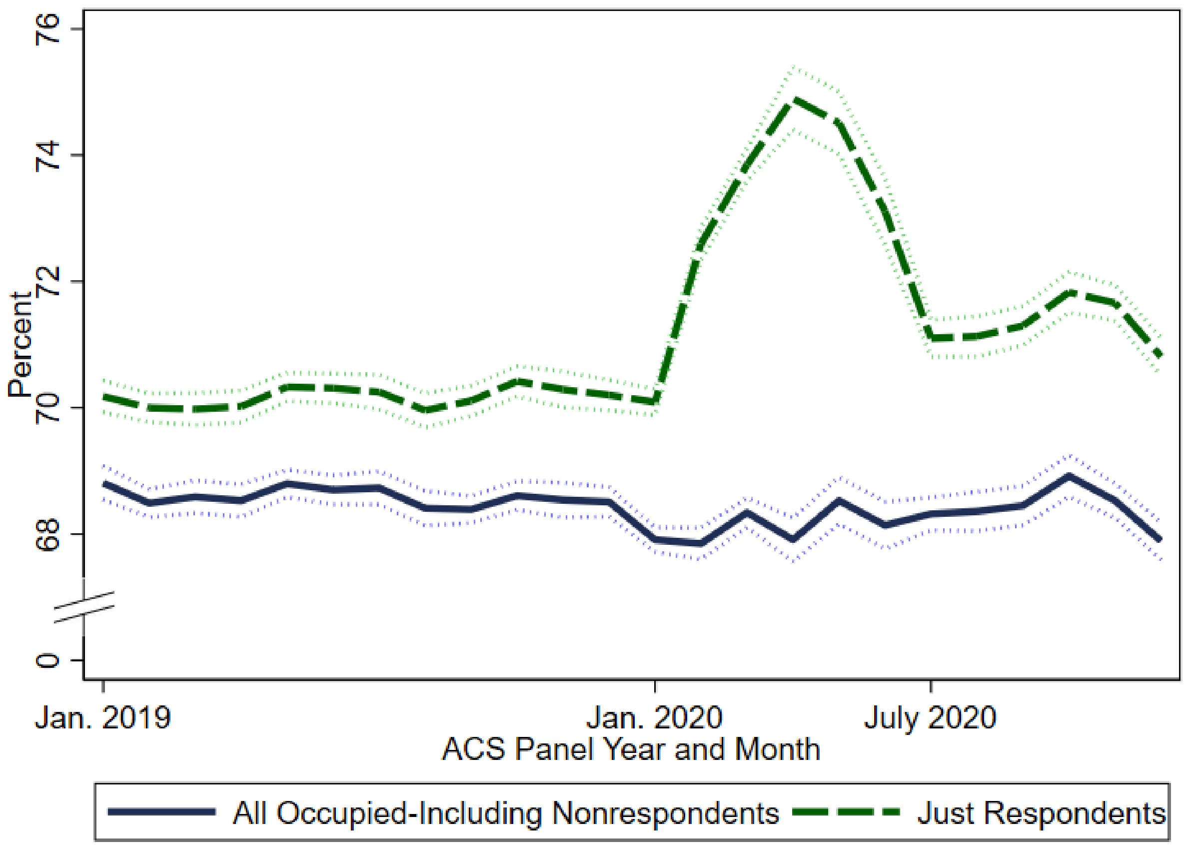
Notes: This figure is a graphical representation of the linkage for the decennial census, administrative, and third-party data used in this paper. First, addresses are linked to individuals using the files in the oval to construct an administrative data roster of individuals for each occupied housing unit in the survey. Then, those individuals and addresses are linked to other datasets using the unique identifiers associated with each arrow in the diagram.

3.3 Comparing Respondents and Nonrespondents

Using the administrative data described above, we examine how the characteristics of ACS respondents changed in 2020 to motivate the need for an alternative weighing methodology. While the year-to-year changes in Section 2.3 suggest increased nonresponse bias, the following analysis using direct data on ACS nonrespondents will help provide further evidence. We first focus on the percentage of occupied units that are single-family homes, as indicated by the structure-type variable on the MAF. The distribution of structure type changes little from year to year, so any changes in estimates over time are more likely due to changes in response behavior. Figure 2 plots the estimate from the sample of all occupied housing units in the ACS, including both respondents and nonrespondents, as well as the estimate received from only respondents in occupied housing units. The horizontal axis gives the month a household was sampled for the ACS.[13] Thus, this graph describes how representative the ACS respondent sample is before any weighting adjustments designed to reduce nonresponse bias. For more details on how respondents and nonrespondents in the ACS compared to each other in the 2010s, please refer to Eggleston (2020).

[13] The weights used in this graph account for the ACS base weight and CAPI subsampling factor adjustment discussed in Section 4 and Appendix A.

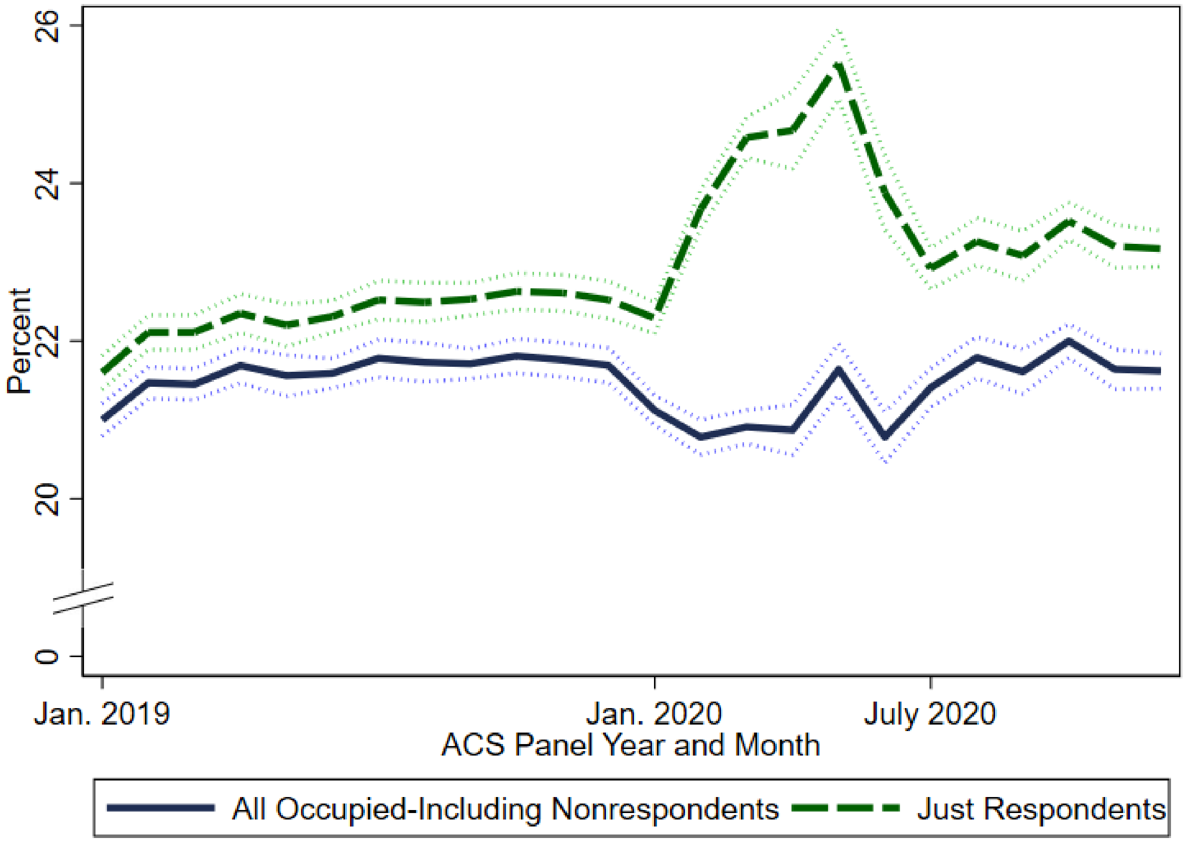
Figure 2: Nonresponse Analysis of Single-Family Homes



Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to the Master Address File.
Note: 90-percent confidence interval shown around each line. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](https://www.census.gov).

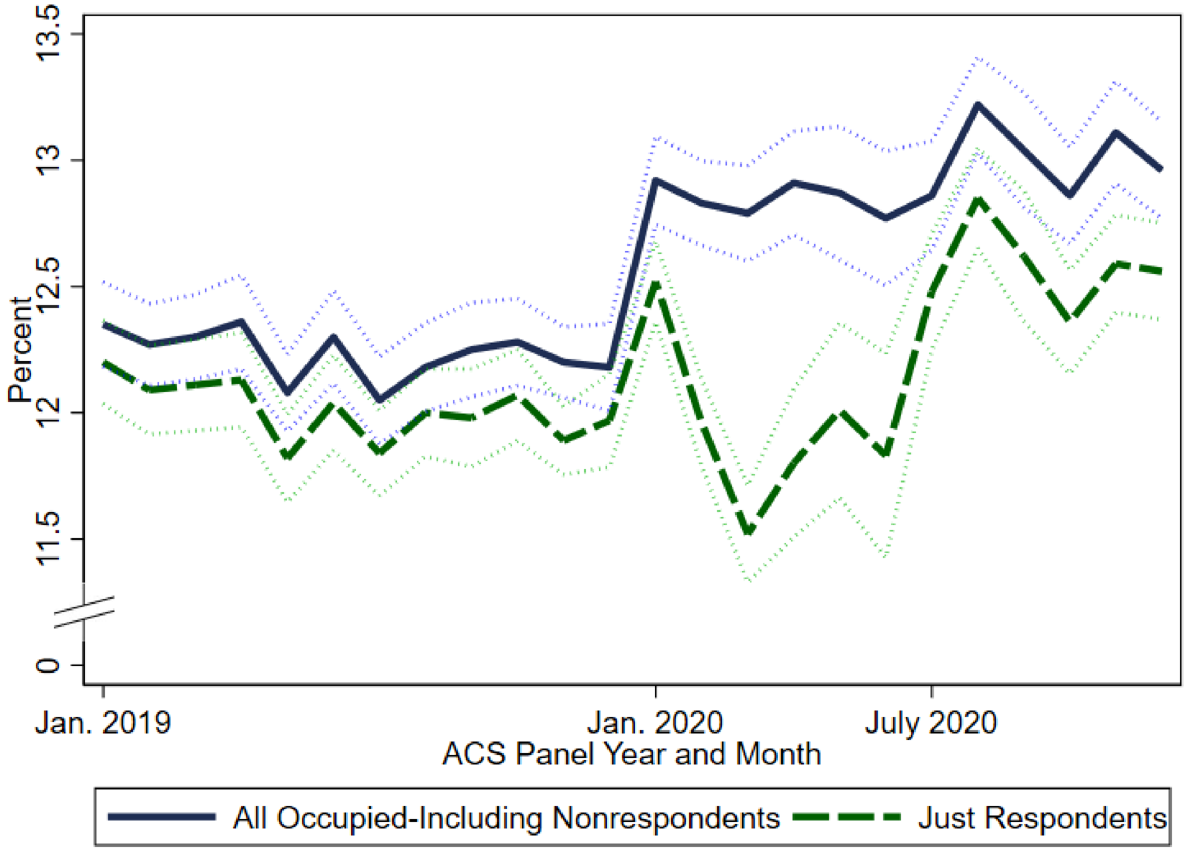
Figure 2 shows that even before the COVID-19 pandemic, respondents were more likely to live in single-family homes than the general sample. In 2019, the percentage of respondents in single-family homes was about 70 percent, compared to about 68.5 percent for the sample of occupied units. However, in 2020, the differences were even larger, peaking in April 2020 with 74.9 percent of respondents in single-family homes. Even in the July to December 2020 panels, when in-person interviewing had resumed in most geographic areas, 71 percent of respondents lived in single-family homes, a rate still higher than the 2019 average.

Figure 3: Nonresponse Analysis of Household W-2 Earnings Over $100,000



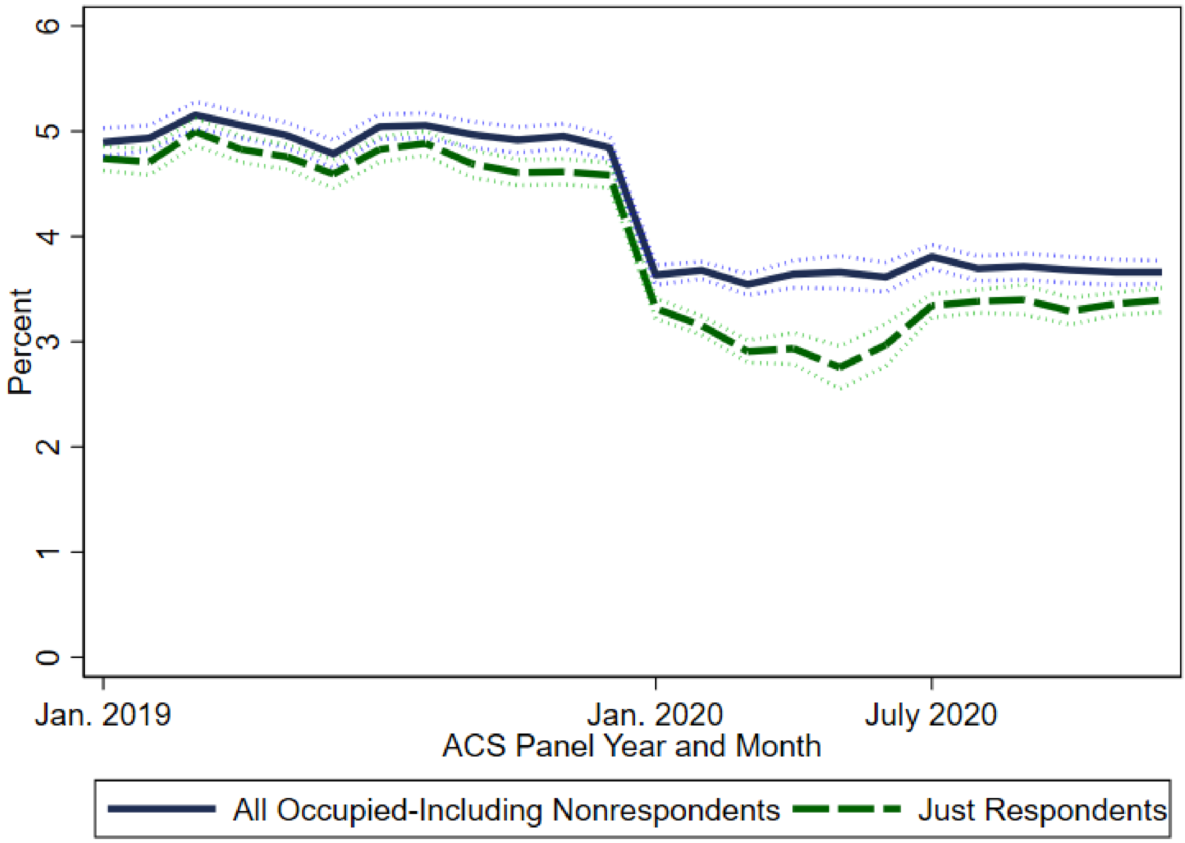
Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data are linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)].

Figure 4: Nonresponse Analysis of Household W-2 Earnings Between $1 and $25,000



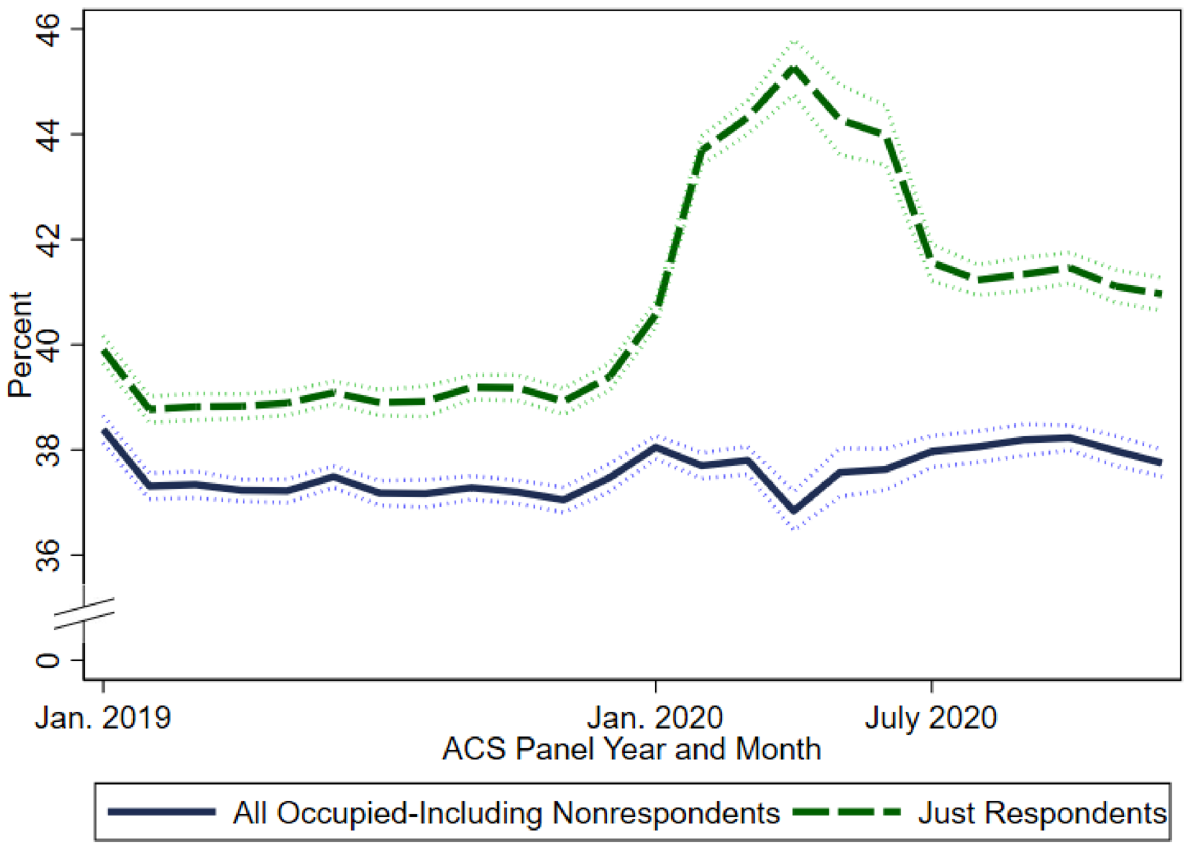
Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data are linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Figure 5: Nonresponse Analysis of Presence of Worker in Household with Four or More Jobs



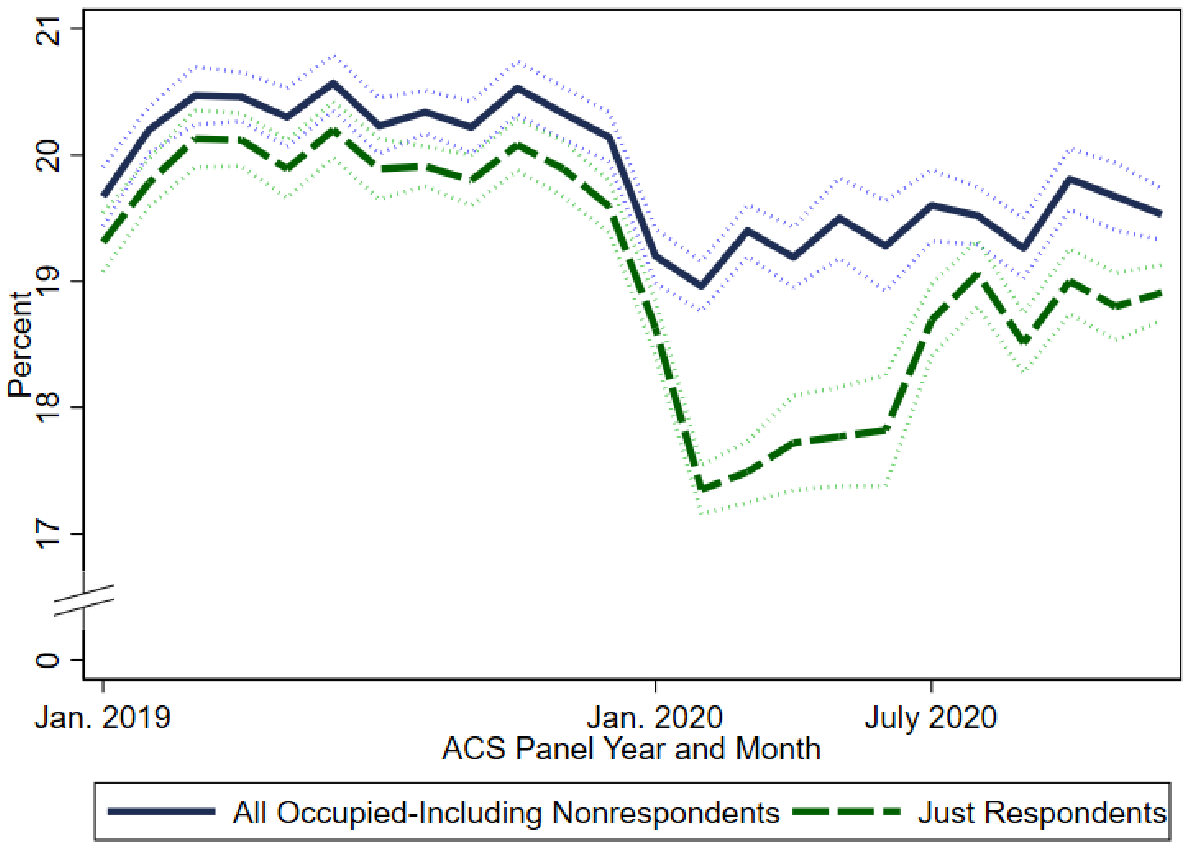
Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data are linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Figure 6: Nonresponse Analysis of Presence of Household Member Aged Over 60 Years



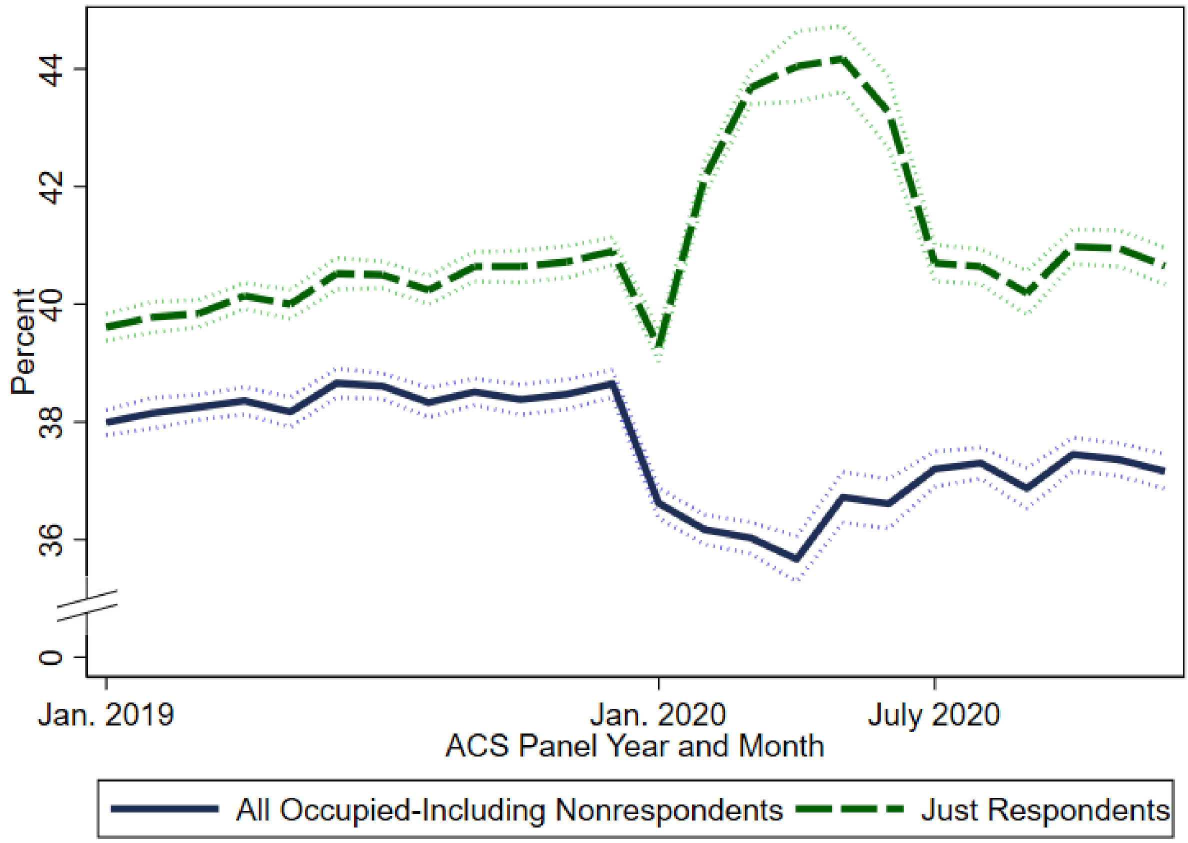
Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data are linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Figure 7: Nonresponse Analysis of Presence of Household Member Aged Under 10 Years



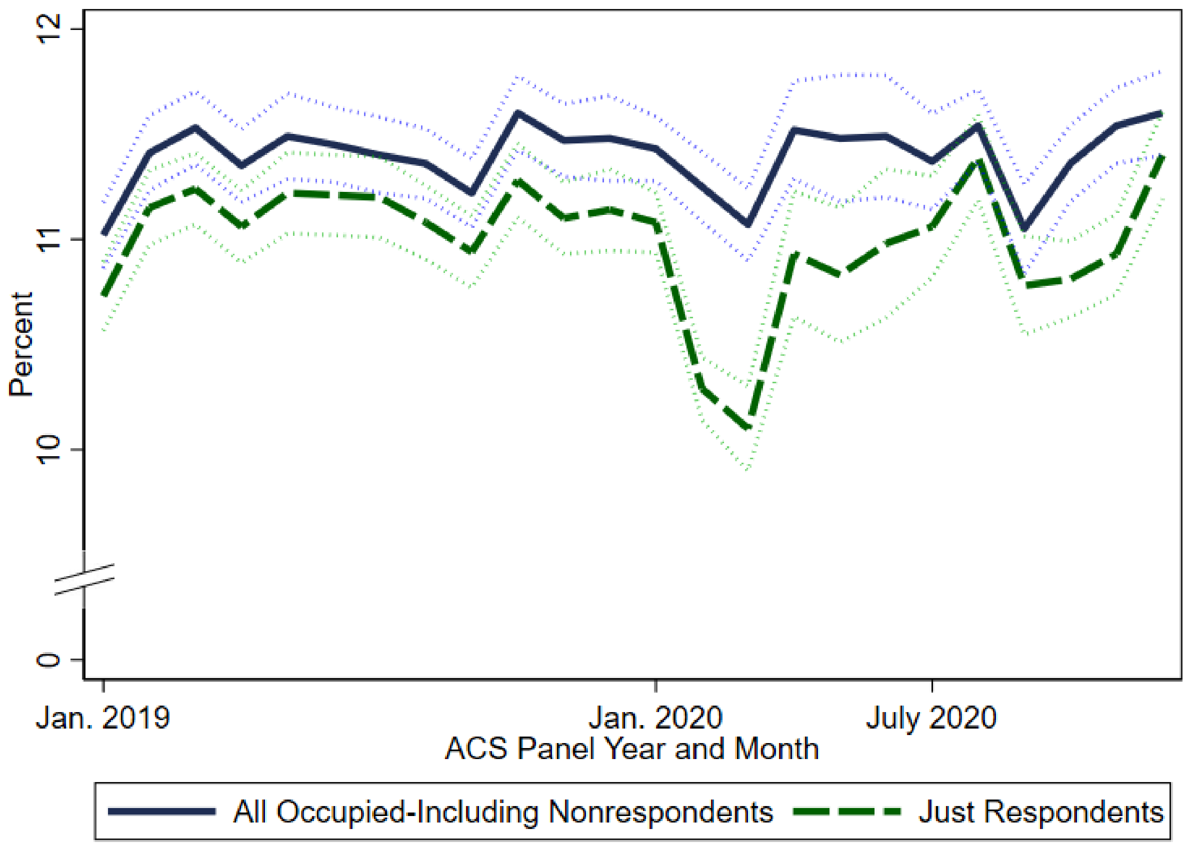
Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data is linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Figure 8: Nonresponse Analysis of Households with a Married Couple



Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. In this graph, filing status from IRS 1040 tax returns is used as a proxy for marital status. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data are linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](https://www.census.gov).

Figure 9: Nonresponse Analysis of Households with a Noncitizen



Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data matched to Internal Revenue Service data and other administrative data as described in Section 3.2.
Notes: 90-percent confidence interval shown around each line. For each panel year, the linkages to administrative and third-party data can change. For example, the January through December 2019 data are linked to tax year 2019 W-2 earnings, and the January through December 2020 data are linked to tax year 2020 W-2 earnings. As a result, there can be discontinuous level changes in estimates in January 2020 for all occupied housing units, including nonrespondent and respondent units. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)].

This deterioration in the representativeness of the ACS sample is not confined to building type. Figures 3 through 9 show similar graphs for demographic and income measures, as inferred from our administrative data. These figures shows that even in 2019, respondents

- had higher income,
- were less likely to have multiple jobs,
- were more likely to have a household member over 60,
- were more likely to be married, and
- were less likely to have a child under the age of 10.

In 2020, however, these existing differences were exacerbated.

4. ACS Sampling and Weighting

The ACS has procedures in place to address nonresponse bias in the respondent sample and adjust for it using survey weights, which we describe briefly.[14]

4.1 ACS Sample Design

As noted above, the Census Bureau's MAF contains all residential and group quarters addresses in the United States. The annual ACS housing unit sample is selected from the universe of all valid residential addresses in the MAF. The probability of selection for each unit is a function of the estimated number of occupied housing units in a geographic entity (census tract, county, school district, Tribal Subdivisions, etc.) as well as predicted self-response rates for that geography. Selected units are randomly assigned a panel month.[15]

As noted in Section 2, the ACS has three modes of data collection: 1) Internet, 2) mail, and 3) CAPI.[16] Households that did not respond by Internet or mail within two months can be selected for in-person CAPI follow up. The selection probability varies from 33 to 50 percent based on prior predicted tract-level Internet and paper self-response rates.

4.2 Weighting Adjustments for Nonresponse

Sampled housing units are assigned a base weight based on their probability of selection. CAPI households have their base weights adjusted to reflect the results of CAPI subsampling, based on their CAPI selection probability.[17] This is called the CAPI Subsampling Factor (SSF). The SSF is the inverse probability of CAPI selection—for example, 3 if the CAPI selection probability is 33 percent. Prior to 2020, all households who self-responded had SSF values set to 1, so their base weights were not increased. However, some of these households responded after CAPI operations begin and are referred to as "late self-responders." Because the number of late self-responders has increased over time, the Census Bureau had planned, prior to the COVID-19 pandemic, to modify this procedure for the 2020 ACS.[18] For late self-responders who had been selected for CAPI follow-up, the SSF was applied just as for CAPI respondents, increasing late self-responders' weights by a factor of two to three. More details about this can be found in Appendix A.

For the remaining set of weighting adjustments, households are assigned to "weighting areas," which are geographic areas defined from counties. Weighting areas are counties or aggregations of small counties.[19]

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[14] For more information about ACS sampling and weighting, refer to "American Community Survey Accuracy of the Data" (U.S. Census Bureau, 2020).

[15] Households in remote Alaska are assigned randomly to be sampled in January or September.

[16] Households in remote areas of Alaska, certain American Indian and Alaska Native areas, and at addresses that are deemed unmailable are only sampled via CAPI. All remote Alaskan addresses are selected and 2/3 of other unmailable addresses are selected for CAPI.

[17] After April 2020, CAPI selection probabilities were increased, given that fewer sample members were able to self-respond and that interviewers were able to use the time they had spent driving to and from CAPI households to attempt more telephone interviews when in-person interviewing was suspended.

[18] By the December 2018 panel, there were about 32,000 late self-responses from households selected for CAPI interview during the CAPI data collection month, compared with only about 6,100 late self-responses from households not selected for CAPI interview during that month.

[19] Counties with sufficiently large populations form their own weighting areas, with the aggregation determined by whether a county or aggregation of counties had at least 400 expected person interviews in the 2011 ACS. Smaller counties are combined based on the poverty rate, rental rate, density of housing units, demographics (race, ethnicity, age, and sex), distance between county centroids, and Core Based Statistical Area (CBSA) status.

There are 2,130 weighting areas created from the 3,143 counties or county equivalents. Subcounty areas are based on incorporated place and minor civil divisions (MCD).[20]

First, the weights are adjusted for variation in response by month within each weighting area. Next, a non-interview factor is applied to adjust for differences in response rates by building type and tract.[21] Finally, the weights are adjusted to equal the estimated number of housing units in each subcounty area. This yields a weight at the housing unit level for each respondent; the weights of all individuals in a given unit are equal.

Next, the individual weights are adjusted to match the estimated population in their subcounty area. The weights are then assigned a Spouse Equalization/Householder Equalization Raking Factor. This factor is applied to individuals based on the combination of their status of being in a married-couple or unmarried-partner household and whether they are the householder.[22] Finally, a demographic raking factor is applied. This raking factor adjusts individual weights to match the estimates of the population by age, race, sex, and Hispanic origin in each weighting area.

The ACS weights therefore account for selection into sampling and CAPI follow up and selection into response by building type, race, Hispanic origin, age, and gender. While this adjustment is intended to control for some of the observed selection into response noted above, it may not adjust for nonresponse by other characteristics, such as income or multiple job holding.

[20] Subcounty areas are built from incorporated places and MCDs, with MCDs only being used in the 20 states where MCDs serve as functioning governmental units. Each subcounty area formed has a total estimated population of at least 24,000. If two or more subcounty areas cannot be formed within a county, then the entire county is treated as a single area.

[21] The building-type adjustment uses information on single- and multi-unit buildings from the MAF.

[22] From the ACS technical documentation, "One person in each household is designated as the householder. In most cases, this is the person or one of the people in whose name the home is owned, being bought, or rented and who is listed on line one of the survey questionnaire. If there is no such person in the household, any adult household member 15 years old and over could be designated as the householder." More information is available at https://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2019_ACSSubjectDefinitions.pdf, accessed 8/2/21.

5. Constructing New Weights

To further address nonresponse bias in the ACS, we would like to add additional information not available in the survey, specifically from the linked decennial census, administrative, and third-party data. We use entropy balancing (Hainmueller, 2012), an application of exponential empirical calibration (Deville and Särndal, 1992), which has also been applied to the CPS ASEC to address nonresponse bias during the pandemic, by Rothbaum and Bee (2021).[23] Entropy balancing estimates the set of weights that matches a specified set of balance constraints, while minimizing the distance between the initial and final weights.

5.1 Entropy Balance Weights

Suppose we have n observations, where $i = 1, 2, \dots, n$ with base weights $q = \{q_1, q_2, \dots, q_n\}$, in our case determined by the sampling probability. Entropy balancing estimates the set of weights $w = \{w_1, w_2, \dots, w_n\}$ that solve the following minimization problem:

$$\min_{\mathrm{w}} \sum_{i=1}^{n} w_i \log\left(\frac{w_i}{q_i}\right) \tag{1}$$

subject to several sets of constraints. First, we have J balance constraints, where $j = \{1, \dots, J\}$. Let $X = \{X_1, \dots, X_J\}$ be a matrix of observable characteristics. For each characteristic j, the balance constraint is defined to match a pre-specified constant $\bar{c}_j$, where:

$$\sum_{i=1}^{n} w_i c_j(X_{i,j}) = \bar{c}_j. \tag{2}$$

$c_j(\cdot)$ can be any arbitrary function.

Second, we have constraints on the weights themselves:

$$\sum_{i=1}^{n} w_i = \bar{w} \tag{3}$$

$$w_i \geq 0. \tag{4}$$

These ensure that the weights are non-negative and sum to some pre-specified total weight $\bar{w}$, which can be the population count or 1. The value of $\bar{w}$ does not affect the relative weights of each observation.

As such, the weights can be adjusted to match specified moments such as population means, variances, higher-order moments, moments of any transformed distribution of $X_{i,j}$, etc. In summary, entropy balancing adjusts the weights according to (1), subject to the constraints in (2), (3), and (4).[24]

As noted above, entropy balancing was developed for estimating causal treatment effects in observational studies. Zhao and Percival (2017) show that, in that context, entropy balancing is equivalent to estimating a logistic model for the propensity score and a linear regression model for the outcome, conditional on the covariates used in the balance constraints. They find that entropy balancing is doubly robust---if at least one of the two models is correctly specified, the estimated population average treatment effect on the treated (PATT) is consistent.

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[23] The discussion of entropy balancing in this section very closely matches the discussion in Rothbaum and Bee (2021).

[24] In practice, as it is not necessarily possible to satisfy all constraints simultaneously through weighting adjustment, the analyst sets a tolerance level for the moment constraints. The weighting algorithm adjusts the weights iteratively until all constraints are satisfied subject to the specified tolerance.

Using the notation of that literature, let γ be the PATT, Y be an outcome of interest where $Y(1)$ is the outcome if treated, and $Y(0)$ is the outcome if untreated. Then:

$$\gamma = E[Y(1)|T = 1] - E[Y(0)|T = 1] \tag{5}$$

In the causal inference literature, the challenge is that $E[Y(0)|T = 1]$ is not observed. Under entropy balancing, given $\sum_{i=1}^{n} q_i = \bar{q}$, the PATT is estimated as:

$$\hat{\gamma}_{ebw} = \frac{1}{\bar{q}} \sum_{T_i=1} q_i Y_i - \frac{1}{\bar{w}} \sum_{T_i=0} w_i Y_i \tag{6}$$

In the case of survey weights, response could be thought of as the "treatment," where the double robustness result still holds. Entropy balancing reweights the sample so that the estimate of Y for the weighted respondents is equal to the estimate of Y for the population,[25] or:

$$E[Y] = \frac{1}{\bar{w}} \sum_{i=1}^{n} w_i Y_i. \tag{7}$$

Entropy balancing has several other appealing features for this application. The first is flexibility. Inverse probability weighting (or any simple regression-based reweighting technique) is only amenable to matching characteristics of the distribution in the sample, but not external targets. Entropy balancing and other methods of empirical calibration, on the other hand, will adjust the weights to match any properly specified target moment, whether that balance constraint was estimated from the sample or with external data. The second is statistical efficiency, which is achieved by keeping the final weights as close as possible to the initial probabilities of selection through the inclusion of w_i/q_i in (1). The third is computational efficiency—entropy balancing allows matching to a high-dimensional vector of moment constraints. Fourth, entropy balancing directly adjusts the weights to the balance constraint, as with other empirical calibration methods but unlike single-index propensity score reweighting approaches (such as inverse probability weights). In propensity score approaches, the adjustment is made to the single index generally estimated from a regression. The resulting balance must be assessed to evaluate the success and quality of the propensity score model. In some cases, a misspecified propensity score model can make balance worse on a given set of dimensions. As entropy balancing directly targets those moments, balance is assured. Finally, entropy balancing ensures the weights are strictly non-negative, as the loss function, Equation (1), is not defined for negative weights.

5.2 Applying Entropy Balancing to the ACS

We would like to reweight the respondent sample so that its distribution of characteristics matches the target population from which the sample was drawn. However, some characteristics are not observable for all housing units with the available linked decennial census, administrative, and third-party data. For example, we do not observe any demographic information for housing units that are not linked to any administrative data. Therefore, we use a second source of data for our reweighting: external estimates of population by geography. For both the linked data and the external population estimates, we can specify a set of balance constraints, which are intended to capture the distribution of characteristics in the target population.

---

[25] Conditional on strong ignorability $(Y(0), Y(1) \perp T|X)$ and overlap $(0 < P(T = 1|X) < 1)$, from Rosenbaum and Rubin (1983), as well as the proper specification of the moment conditions required for the Zhao and Percival (2017) double robustness result.

Our data have several additional complications, however. First, the ACS randomly samples households each month, but households selected in the same month can respond at very different times. For example, the set of households selected for contact during 2020 does not match the households that are in the 2020 ACS sample, as some 2020 respondents were selected in 2019. To address this, we estimate the target moment conditions on the sample of occupied housing units selected in that year (some of which respond the next year) and use those constraints to adjust the weights of the given year's respondents. As an example, we would estimate the moments of the distribution of W-2 earnings of occupied housing units that were selected for the ACS in 2020. We would then adjust the weights of 2020 ACS respondents using entropy balancing so that their weighted W-2 earnings matches those separately estimated moments.

Second, the target moments are at separate levels of aggregation. Estimates from the linked decennial census, administrative, and third-party data are at the housing-unit level, whereas the state- and county-level population moments are at the individual level. Entropy balancing is not amenable to matching moments at different levels of aggregation. Therefore, we proceed with a two-stage reweighting procedure. We describe the procedure below and summarize it in Table 1. This is analogous to two-step calibration, as discussed in Estevao and Särndal (2006).

Table 1: Entropy-Balancing Reweighting Summary

Stage/Step	Balance Constraints: Estimation Sample	Balance Constraints: Weights Used	Balance Constraints: Variables	Reweighted Sample
1. Housing-Unit level	Nonvacant housing units selected to be contacted in a given year (the Panel Year sample).	Base weights adjusted for CAPI sampling	Housing-unit level summary statistics from the linked census, administrative, and third-party data, including race, Hispanic-origin, earnings (level and change from prior year), income, firm industry, marital status, and characteristics of the housing unit.	Respondent housing units
2. Person Level				
A. Preserve distribution of housing unit characteristics	Respondent sample	Stage 1 housing-unit weights	Housing-unit level summary statistics from the linked census, administrative, and third-party data, including race, Hispanic-origin, earnings (level and change from prior year), income, firm industry, marital status, and characteristics of the housing unit.	Respondent sample
B. Spousal equivalence	Respondent sample	N/A	Housing-unit level summary statistics from the linked census and administrative data, including race, Hispanic-origin, earnings, and income.	
C. External population targets	External estimates	Production survey weights (as estimated from estimates)	Occupied housing units, age, race, Hispanic-origin, gender, and county-level age and race statistics.	
D. Monthly balancing	Respondent sample	Stage 1 housing-unit weights	Balance weights so that each month has 1/12th of the weight. Adjust within-month weights to match annual housing-unit level estimates of earnings (level and change from prior year) and income.	

Notes: This table describes the two-stage entropy balance reweighting procedure. In the first stage, respondent housing units are reweighted to control for selection into response. This is done by reweighting them to match the characteristics of the target population: nonvacant housing units, excluding late self-responders who were not selected for in-person (CAPI) follow-up. In the second stage, we estimate individual weights that preserve the distribution of housing-unit characteristics from the first stage, while also matching external population totals preserving a notion of spousal equivalence and balancing the weights within and across months.

For each year t of ACS data, we start with two ACS samples, both linked to the census, administrative, and third-party data. The first sample includes housing units that were selected for the ACS in year t, which we call the panel year (PY) sample. These households may have responded year t or year $t+1$. The second sample is the set of households responding in year t, which we call the respondent year (RY) sample, which could have been in selected for sampling in panel year t or $t-1$.

For the PY sample, we start with the base weights, which reflect only the probability of selection. We then apply our own CAPI SSF adjustment.[26] Our SSF adjustment is applied to all households sampled for CAPI and excludes all households not sampled for CAPI. Unlike the SSF adjustment introduced for 2020 ACS production weights, our adjustment removes households who self-responded, but only after the Census Bureau decided to not follow up with them during CAPI operations.[27] This gives us an adjusted base weight (q_i) for all occupied housing units that were sampled in that year. While our modified SSF procedure does result in a smaller sample size than the standard SSF procedure planned for 2020, it offers the benefits of removing some of the complications resulting from the ACS's CAPI subsampling procedures. We consider this tradeoff acceptable for the purpose of constructing moment condition targets because it should help ensure that we have a representative sample of occupied housing units Additionally, nonresponding addresses' occupancy status remained unknown after CAPI operations more often in 2020 than in prior years because interviewers were unable to physically visit a greater proportion of those addresses than usual. To aid the weighting adjustments, the model described in Keller et al. (2018) and developed to predict occupancy status for the 2020 Census was applied to the 2020 ACS, as summarized in U.S. Census Bureau (2021). We use the imputed occupancy status produced by this model to create our sample of occupied households.

For the RY sample, we use the initial base weights that reflect the sampling probability as the base weights for the entropy balancing adjustment. We apply the SSF according to the standard procedures planned for 2020, which give positive weight to late self-responders who were not subsampled for CAPI.

Let $X_{i,j}^L$ be characteristic j for household i. In the linked decennial census, administrative, and third-party data (denoted by the L superscript), let O_k be the set of occupied housing units and R_k be the set of respondent housing units, with $k = \{PY, RY\}$, which indicates ACS panel year or respondent year sample. For simplicity, assume that the weights are normalized to sum to 1. We estimate the first-stage weights w_i^1 using entropy balancing, where the target on the right-hand side of constraint equation (2), our constant $\bar{c}_j$, is estimated from the panel year sample of occupied housing units:

$$\sum_{i \in R_{RY}} w_i^1 c_j\left(X_{i,j}^L\right) = \sum_{i \in O_{PY}} q_i^{PY} c_j\left(X_{i,j}^L\right). \tag{8}$$

An important caveat is that many characteristics $X_{i,j}^L$ are only observed if we can link individuals to household i. However, for some households, we cannot link any individuals to that address. To address those cases as best we can, we include an indicator variable for any linkage in our set of X^L variables.

[26] Our CAPI SSF adjustment differs from the method used in the 2020 ACS production weights. For a thorough description of the production and our experimental SSF adjustment methods, refer to Appendix A

[27] The SSF adjustment increases the weights of CAPI households to account for the set of all households that did not respond to that point. That set of households includes those that later self-responded but were not selected for CAPI follow up. By dropping those households from our PY sample, we avoid "double counting" those non-CAPI late self-responders.

In the second stage, we create adjusted weights (denoted $w_{p,i}^2$ given individual p in household i and where $p = \{1, \ldots, P^{RY}\}$) to match externally estimated population controls while maintaining the moment conditions targeted in the first stage. We do so by matching four additional sets of balance constraints:

A. Preserve distribution of housing unit characteristics
B. Spousal equivalence
C. External population targets by age, race, sex, and Hispanic origin
D. Monthly balancing

In the first set of constraints (2.A. in Table 1), we calculate per-person weighted moments from the stage-1 weights. Given the number of people in household i, n_i^{HH}, we define the moment condition, with the balance constraints defined using the stage-1 weights:

$$\sum_{p=1}^{P^{RY}} w_{p,i}^2 \frac{1}{n_i^{HH}} c_j\left(X_{i,j}^L\right) = \sum_{i \in R_{RY}} w_i^1 c_j\left(X_{i,j}^L\right). \tag{9}$$

As above, the term on the right-hand side is treated as the constant $\bar{c}_j$. This ensures that if we take the average weight of household members in household i (HH_i) as $\overline{w}_i^2 = \frac{1}{n_i^{HH}} \sum_{p \in HH_i} w_{p,i}^2$ the stage 2 weights will satisfy the following condition:

$$\sum_{i \in R_{RY}} \overline{w}_i^2 c_j\left(X_{i,j}^L\right) = \sum_{i \in R_{RY}} w_i^1 c_j\left(X_{i,j}^L\right). \tag{10}$$

This does not require that $\overline{w}_i^2$ is equal to w_i^1 for any household i, just that the specified constraints from stage one hold in the final Entropy balance weights (EBW) weights, when the final weights are averaged across all household members. This procedure of dividing the household moments equally among the family members helps ensure that each person contributes to satisfying the moments from linked decennial census, administrative, and third-party data, which should reduce the variability of weights among household members. This can be particularly important for person-level statistics, such as poverty.

For our second set of constraints (2.B. in Table 1), we apply a spousal equalization adjustment that mimics the kind of spousal equalization done in the ACS and CPS ASEC weights. These ensure that, for the included characteristics, the estimate of $c_j\left(X_{i,j}^L\right)$ is invariant to being weighted by one spouse or the other. This is desirable for couples that co-own or co-rent their residence, as which spouse is denoted as the head depends on who is listed first on the household roster. This procedure reduces weighting sensitivity to this arbitrary distinction. Let $S = \{0, 1, 2\}$, where $S = 0$ if an individual is unmarried,[28] 1 if the individual is the first spouse or cohabiting partner on the file, or 2 if the individual is the second spouse or partner on the file. Given an indicator function $I(\cdot)$, the spousal equivalence moment conditions are of the form:

$$\sum_{p=1}^{P^{RY}} I(S=1) w_{p,i}^2\, c_j\left(X_{i,j}^L\right) - I(S=2) w_{p,i}^2\, c_j\left(X_{i,j}^L\right) = 0. \tag{11}$$

This does not require that each individual's weight be equal to his or her partner's, as that would require a separate moment condition for each couple.

[28] Or the spouse or partner is not present or cannot be imputed from the household roster, relationship variable, and relative ages.

Next, we include a third set of constraints to adjust the weights to match external estimates of race, Hispanic origin, age, and gender (2.C. in Table 1).[29] This is analogous to the raking adjustment done in the ACS and CPS ASEC weights. For a given demographic characteristic $X_{p,j}^{D}$ for individual p given an external estimate $\bar{c}_j^D$, these moment conditions are of the form:

$$\sum_{p=1}^{P^{RY}} w_{p,i}^2 c_j\left(X_{p,j}^D\right) = \bar{c}_j^D. \tag{12}$$

With these three sets of constraints, we would reweight the respondent year sample of the ACS to match estimates of the characteristics of all occupied housing units in the panel year sample (using the linked data) and the external estimates of population demographics.

However, the ACS is a rolling sample with households answering the survey in different months. The ACS includes questions about economic conditions during rolling reference periods.[30] Therefore estimates in the 1-year ACS file are often weighted averages of the economic conditions during the different reference periods for each respondent. This is of particular importance during the unprecedented economic fluctuations of the COVID-19 pandemic.

In a normal year (absent a pandemic or government shutdown affecting data collection), there is slight variation in the share of the sample in each month, after the ACS monthly weighting adjustment. For example, in 2018, there are 3.6 percent more weighted respondents with interviews in January and 4.9 percent fewer weighted respondents with interviews in December than if each month had 1/12th of the weighted respondents. However, in 2020, the unweighted sample of respondents with interviews in April and May are 66 and 57 percent smaller, respectively, than would be the case if each month had 1/12th of the unweighted respondents. This gives much greater weight to economic conditions as reported by respondents in January, February, March, and September (months with higher than 1/12th the total weight) than conditions in April, May, and June.

To address this issue, we create a fourth set of moment conditions that set the sum of the weights in each month to equal 1/12th the total weight (2.D. in Table 1). Given a month of interview dummy $D_{p,m}$, which is equal one if individual p responded in month m, the condition is:

$$\sum_{p=1}^{P^{RY}} D_{p,m} w_{p,i}^2 = \frac{1}{12}. \tag{13}$$

However, the variation in response by month could also reflect nonrandom selection into response. We therefore add conditions to reweight the sample within each month to make each month's sample more representative. We do so by matching a subset of characteristics from the linked decennial census, administrative, and third-party data in each month. These conditions are monthly versions of (9), scaled by 1/12:

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[29] Specifically, in our implementation, we directly use county- and state-level population estimates of cells defined by interactions of race and Hispanic origin, gender, and age from the production weights in the ACS. However, as the ACS raking procedure is designed so that these totals match external population controls, we are indirectly matching to those same external population controls.

[30] For example, respondents are asked about their employment status last week and their income in the prior twelve months ("the period from today's date one year ago up through today").

$$\sum_{p=1}^{P^{RY}} \frac{1}{n_i^{HH}} D_{p,m} w_{p,i}^2 c_j\left(X_{i,j}^L\right) = \frac{1}{12} \sum_{i \in R_{RY}} w_i^1 c_j\left(X_{i,j}^L\right). \tag{14}$$

For example, suppose that $c_j\left(X_{i,j}^L\right)$ is a dummy that indicates that household i had W-2 earnings below \$25,000. This condition would ensure that the $\overline{w}_i^2$-weighted share of households in each month with W-2 earnings below \$25,000 would match the estimated share of households with earnings below \$25,000 in the sample of all occupied housing units, denoted by $\sum_{i \in O_{PY}} q_i c_j\left(X_{i,j}^L\right)$ from (8). An ACS with weights balanced across months is potentially more useful for assessing within-year changes in economic conditions, as well.

The weighting procedure is run separately for each of the 50 states and the District of Columbia. For the linked decennial census, administrative, and third-party data, and the external population controls, we also include moments for all counties that have populations greater than 65,000. The weights estimated from this procedure are the new "experimental" weights.

5.3 Standard Errors

For valid inference, we repeat the two-stage reweighting procedure an additional 80 times, using the base weight replicate factors (for the stage-one weights). These base weight replicate factors account for the sample design of the ACS. We also use the regularly produced replicate weights for the population controls in Section 2.C of Table 1 to account for the uncertainty in these controls, as incorporated into regular ACS production. This allows us to properly account for the uncertainty in our estimates given the uncertainty in the underlying distributions of the linked decennial census, administrative, and third-party data and population estimates. All standard errors reported for estimates using the new, entropy balance weights are calculated with these new replicate weights.

In addition to changing the point estimates, the entropy balance weights also affect the standard errors of the estimates. It is generally understood that increased variability among the survey weights can increase the standard errors, so weighting adjustments aimed at reducing bias are often done at the expense of increasing variance. However, Little and Vartivarian (2005) show that this may not hold true if the variable used to adjust for nonresponse is correlated with the survey variable of interest, a property they call "super-efficiency."

For example, by reweighting respondents to match moments of the administrative income distribution among all occupied housing units, the standard error for reweighted estimates of survey income will be reduced because administrative income is highly correlated with survey income responses. Prior work has found similar effects. For example, Eggleston and Westra (2020) construct administrative-data-based weights for the SIPP and find that the standard error for median earnings at the national level decreased by 35 percent, although this decrease was not statistically significant. Rothbaum and Bee (2021) find that entropy balance weights in the CPS ASEC reduce the standard error for median household income in 2020 by 50 percent. Standard errors will also narrow for other variables that are not targeted using the linked data, but which are correlated with information that is targeted. For example, we do not have linked data on the education of respondents and nonrespondents. However, if education is correlated with income, homeownership, marital status, and other variables that we can target using the linked data, then the standard error on survey estimates of education will also be reduced through reweighting.

In summary, it is important to note that the change in weighting methodology for the entropy balance weights should affect the margins of error in addition to affected point estimates. Even though the 2020

ACS sample was smaller because of lower response rates, margins of error for 2020 ACS estimates might not be larger than prior estimates if the weighting counteracts the effects of a smaller sample size.[31]

5.4 Validation

Appendix Tables 5 and 6 show statistics for the 2019 and 2020 ACS illustrating how well the survey weights and entropy balance weights match to targets in the 2010 Census, administrative, and third-party data, where the targets are estimated using the base weights for all occupied housing units.

For example, we can examine how our estimates of adjusted gross income at the address level would vary using the survey base weights (from which we generated our weighting targets), the regular survey weights, and our final entropy balance weights. In 2019, median adjusted gross income from 1040 tax filings was 2.4 percent above the baseline target.[32] However, in 2020, the survey-weighted estimate of median adjusted gross income is 15 percent higher than the baseline target. With the entropy balance weights, the point estimates for both years are within 0.2 percent of the target.[33]

Table 2 shows validation statistics for race and Hispanic origin. The entropy balance weights are matched to the regular survey estimates based on the race alone or in combination and Hispanic origin variables, subject to the minimum number of survey observations in a group required for inclusion in the model. As shown in the table, the survey- and entropy-balance-weighted estimates are not statistically different for nearly all the targeted moments—estimates of race (alone or in combination) and Hispanic origin.

[31] While we expect a reduction in uncertainty, we plan to study whether our estimates have proper coverage, given the magnitude of the change in the margins of error.
[32] Note that a median cannot be a target moment of the reweighing procedure as it is not a linear function of the individual values as required in Equation 2.
[33] These have not been tested to determine if the percent differences between the EBW and base-weighted estimates are different from each other in 2019 and 2020.

Table 2: Race and Hispanic Origin Validation

	2019		2020		Difference (EBW - Survey)		Year-to-Year Change		
	Survey	EBW	Survey	EBW	2019	2020	Survey	EBW	Diff-in-Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Race (Alone or In Combination)									
White	75.0	75.0	73.4	73.4	Z	Z	-1.61***	-1.61***	Z
	(0.03)	(0.03)	(0.04)	(0.04)	Z	Z	(0.04)	(0.04)	Z
Black	14.2	14.2	14.0	14.0	Z	Z	-0.20***	-0.20***	Z
	(0.01)	(0.01)	(0.02)	(0.02)	Z	Z	(0.02)	(0.02)	Z
American Indian and Alaskan Native	1.7	1.7	2.7	2.7	Z	Z	0.97***	0.96***	Z
	(0.01)	(0.01)	(0.02)	(0.02)	Z	Z	(0.02)	(0.02)	Z
Asian	6.8	6.8	7.0	7.0	Z	Z	0.21***	0.21***	Z
	(0.01)	(0.01)	(0.01)	(0.01)	Z	Z	(0.01)	(0.01)	Z
Native Hawaiian and Other Pacific Islander	0.4	0.4	0.5	0.5	Z	Z	0.02**	0.02***	Z
	Z	Z	(0.01)	(0.01)	Z	Z	(0.01)	(0.01)	Z
Some Other Race	5.5	5.5	14.7	14.7	Z	Z	9.12***	9.12***	Z
	(0.02)	(0.02)	(0.04)	(0.04)	Z	Z	(0.04)	(0.04)	Z
Hispanic	18.4	18.3	18.6	18.6	-0.17***	Z	0.13***	0.30***	0.17***
	Z	(0.01)	Z	Z	(0.01)	Z	Z	(0.01)	(0.01)
Race (Alone)									
White	72.0	72.1	62.8	62.7	0.04***	-0.09***	-9.24***	-9.37***	-0.13***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
Black	12.8	12.8	12.1	12.1	-0.02***	-0.04***	-0.66***	-0.68***	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
American Indian and Alaskan Native	0.9	0.9	1.0	1.0	0.06***	0.02***	0.10***	0.06***	-0.04***
	(0.01)	Z	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	5.7	5.7	5.7	5.8	0.03***	0.06***	0.01	0.04***	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Native Hawaiian and Other Pacific Islander	0.2	0.2	0.2	0.2	Z	-0.01***	Z	-0.01*	Z
	Z	Z	Z	Z	Z	Z	Z	Z	Z
Some Other Race	5.0	4.9	6.8	6.8	-0.11***	-0.01	1.80***	1.90***	0.10***
	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)].
Notes: This table shows estimates of race and Hispanic origin using the survey weights (columns (1) and (3)) and entropy balance weights (columns (2) and (4)). The table also shows the within-year differences (columns (5) and (6)), the year-to-year change in each (columns (7) and (8)), and the difference between columns (7) and (8) as the difference-in-difference in column (9). Race alone or in combination and Hispanic origin variables were included in the weighting model, and in nearly all cases, the entropy-balance-weighted estimates do not differ significantly from the regular survey estimates. Standard errors shown in parenthesis. ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates the estimate rounds to zero at the number of digits shown (0.0 for estimates, 0.00 for comparisons and standard errors).

6. Results

In this section we assess the performance of the new weights by comparison to the standard weights, expected patterns, and external benchmarks. For the sake of transparency, an online appendix offers estimates for both the standard weights and experimental weights in both 2019 and 2020, covering a wider variety of topics than discussed in this paper.

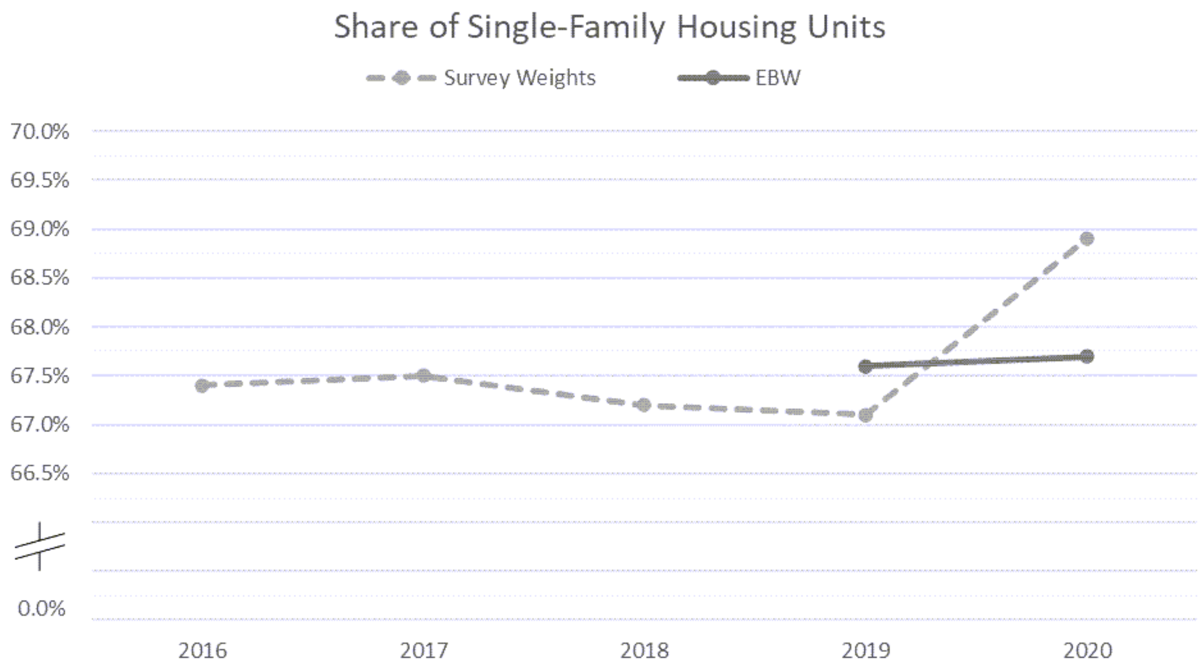
6.1 Housing Characteristics

6.1.1 Building Structure Type

As discussed in Section 2.3, the distribution of structure types of residential buildings (e.g., mobile homes, single-family homes, apartment buildings, etc.) is typically stable and only changes incrementally over time due to changes in residential housing stock (e.g., new construction, demolition, conversion to non-residential uses). Building structure type between 2016 and 2019 changed by no more than 0.4 percentage points between any two years. However, this trend changed markedly for 2020 when estimating building structure type using the 2020 1-year production weights. Specifically, the ACS shows an increase of 1.8 percentage points in the share of single-family housing units (both detached and attached), a decrease of 1.3 percentage points in the share of buildings with 2 or more units, and a decrease of 0.5 percentage points in the share of mobile homes when using the 2020 1-year production weights.

When using the entropy balance weights to calculate both 2019 and 2020 ACS estimates of building structure type, results indicate that structure type follows the expected trend of only incremental change between 2019 and 2020. Specifically, single-family housing units changed by only 0.1 percentage points, from a share of 67.6 percent in 2019 to a share of 67.7 percent in 2020. This change is not statistically significant. Moreover, the share of buildings with two or more units did not change between 2019 and 2020 (26.3 percent). Lastly, the share of mobile homes was 6.1 percent in 2019 and 6.0 percent in 2020. When comparing the 1-year production weights to the entropy balance weights, the entropy balance weights mitigate the changes between 2019 and 2020.

Figure 10: Share of Single-Family (Attached or Detached) Units (2016-2020)



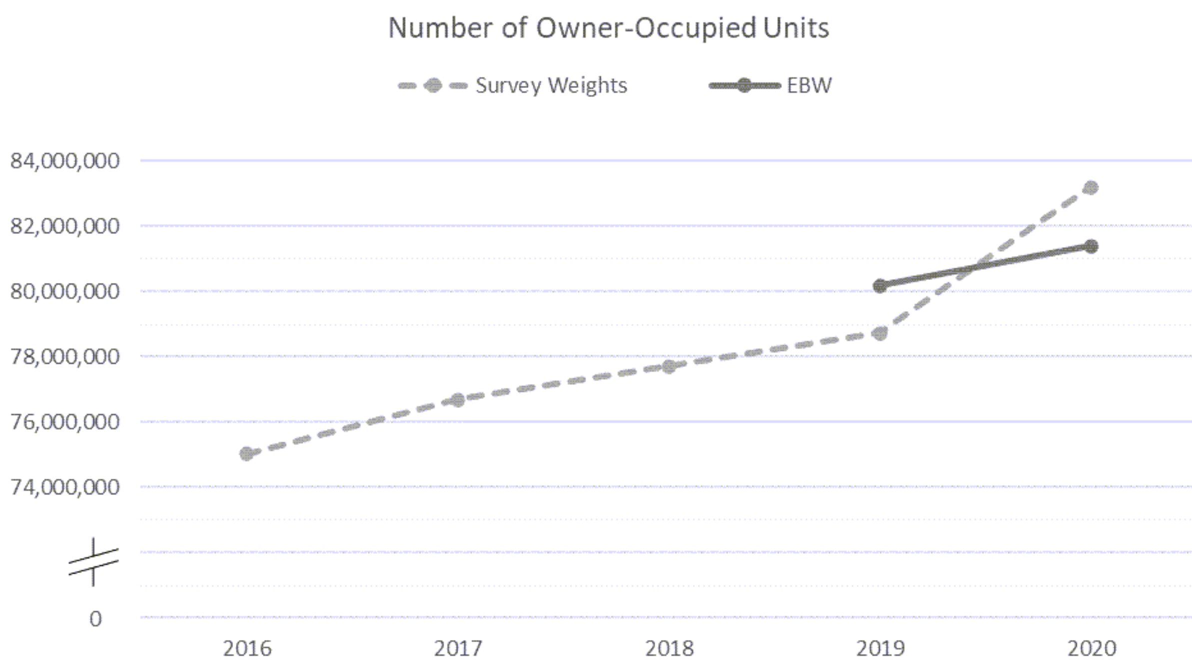
Source: U.S. Census Bureau, 2016 through 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)].
Note: Entropy balance weights (EBW) were only produced for 2019 and 2020.

6.1.2 Housing Tenure

According to the ACS 1-year production weights, the share of owner-occupied housing units increased by 2.8 percentage points between 2019 and 2020. Put another way, the number of owner-occupied units increased by approximately 4.5 million units, while the total number of occupied units only increased by approximately 1.5 million units between 2019 and 2020. This change in tenure between 2019 and 2020 is made even more striking after reviewing the housing tenure trend over the last several years. Specifically, between 2016 and 2019, housing tenure only changed incrementally; the share of owner-occupied units never changed by more than 0.75 percentage points (approximately 1.7 million units) between any two consecutive years from 2016 and 2019. The year-over-year differences between 2019 and 2020 according to the 1-year production weights markedly deviate from that historical trend.

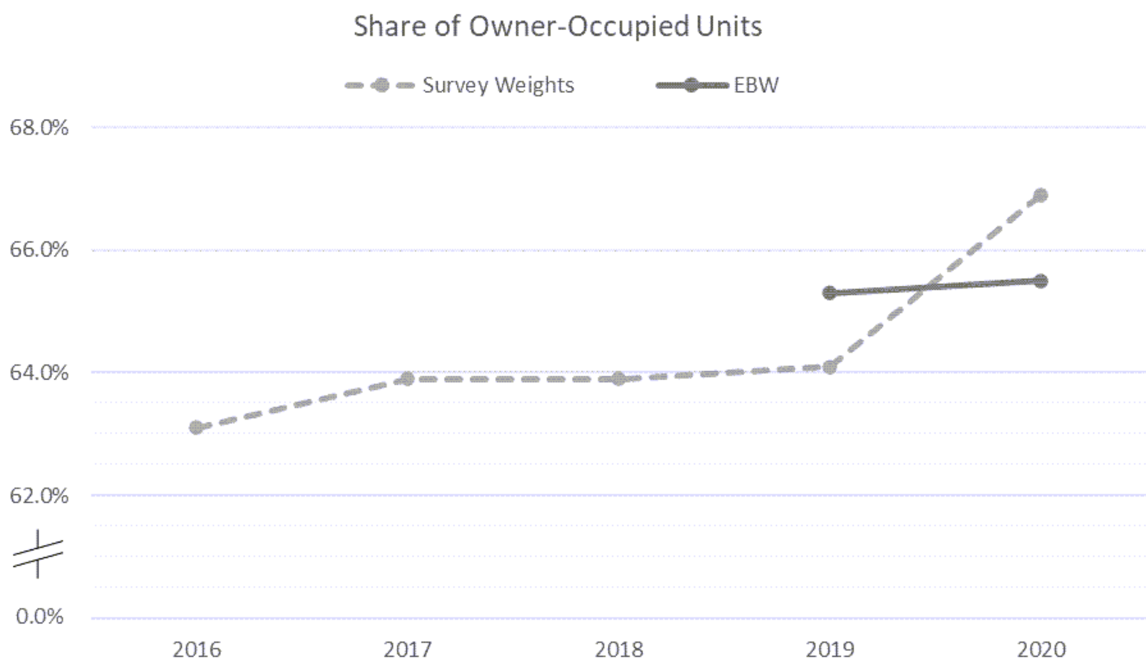
The results of the entropy balance weights paint a very different picture of the differences in housing tenure between 2019 and 2020. When using the new weights for both years, the share of owner-occupied units increased 0.2 percentage points, or approximately 1.2 million units, between 2019 and 2020. This incremental increase in owner-occupied units in 2020 demonstrates change consistent with the historical year-over-year trend in housing tenure. The 2020 entropy balance estimates improve on the 2020 1-year production weights for estimates of housing tenure by mitigating the change between 2019 and 2020 in housing tenure estimates.

Figure 11: Number of Owner-Occupied Units (2016-2020)



Source: U.S. Census Bureau, 2016 through 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Note: Entropy balance weights were only produced for 2019 and 2020.

Figure 12: Share of Owner-Occupied Units (2016-2020)



Source: U.S. Census Bureau, 2016 through 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Note: Entropy balance weights were only produced for 2019 and 2020.

6.2 Social Characteristics

6.2.1 Citizenship

One of the demographic statistics that exhibited suspicious patterns using the production weights for the 2020 ACS 1-year data was the number of noncitizens. As Figure 13 shows, the number of noncitizens declined by about 1.6 million people between 2019 and 2020 when comparing the production-weighted estimates. This stands out against a year-to-year change of no more than 0.5 million in any year between 2012 and 2019 (U.S. Census Bureau, 2021).

In this subsection, we assess whether the entropy balance weights improved upon this suspicious trend. Countervailing factors affect whether one should expect the entropy balance weights to improve upon the production weights for estimates of the noncitizen population. On one hand, we observe citizenship status from the Numident for both responding and nonresponding members of our household rosters, and we include the percentage of households with any noncitizen among the balance constraints in Equation 8.[34] On the other hand, noncitizens could be less likely to work in the formal sector and thus less likely to

[34] As Brown et al. (2018) note, 2.5 million foreign-born individuals appearing in the 2010 Census Numident have missing citizenship status. If any of these individuals are linked to the rosters that we construct for occupied housing units sampled by ACS, we assume they are foreign-born citizens.

appear in IRS data. If, for example, no individual can be linked to a given ACS sample address using the IRS data, this absence of a link is all we observe about that sampled housing unit. We include this information in the weighting model, allowing us to adjust the weights of these unlinked respondent households to match the prevalence of unlinked households among all occupied housing units. However, if noncitizens are a larger share of unlinked nonrespondent households relative to unlinked respondents (and external population controls do not adjust for this difference across race and Hispanic-origin cells), then we will have underestimated the share of the population that are noncitizens.

Additionally, there is some evidence of coverage gaps in the Numident for noncitizens (Brown et al., 2018). For example, only noncitizens with Social Security Numbers appear in the Numident. While many noncitizens do have Social Security Numbers, this sizable coverage gap weakens the correlation between administrative and survey citizenship data. This makes the entropy balancing less efficient, but it does not necessarily make it inconsistent.[35]

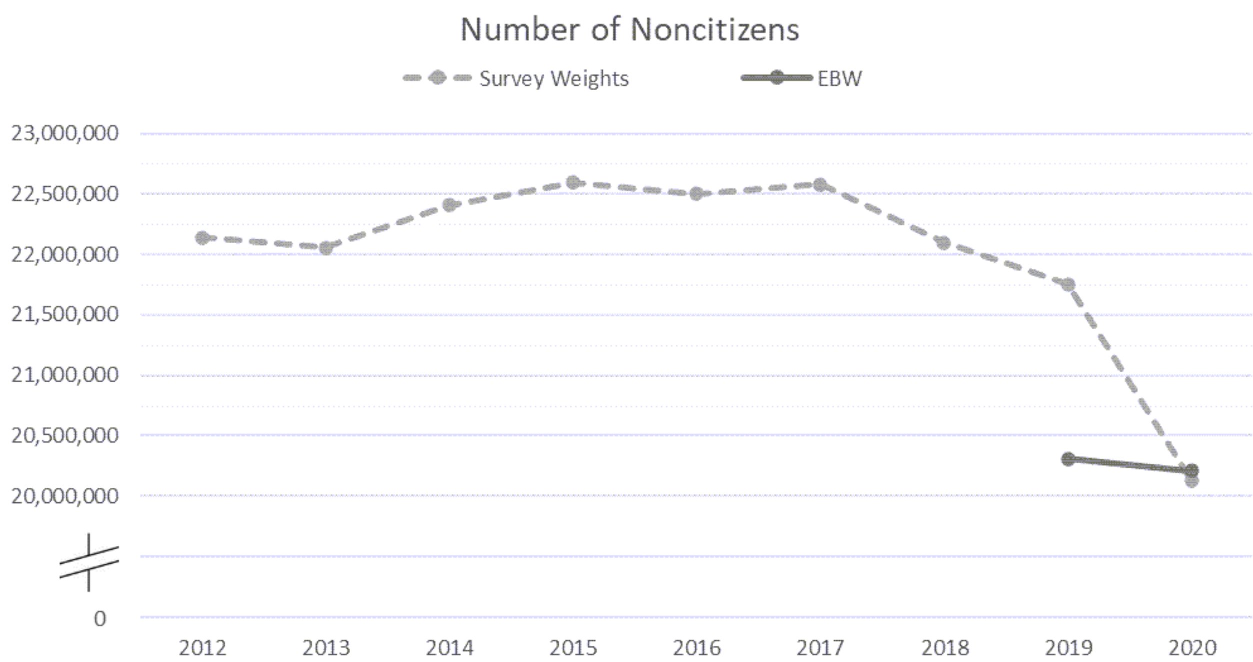
It is important to distinguish between potential data problems that primarily affect efficiency and those that primarily affect the weighting estimator's consistency. The former affects the rate at which the entropy balanced weights converge to reflect respondent's true response propensities (and in particular the relationship between those propensities and the survey variable of interest) as the sample size increases. Issues in the latter category affect whether the model converges at all. For one example, if respondents have a differing relationship between covariates and citizenship than do nonrespondents, the reweighting will be inconsistent. For another example, if response is weakly positively correlated with well-measured income, strongly negatively correlated with poorly measured citizenship, and income and citizenship are strongly positively correlated, the resulting reweighting (mostly on income) could make citizenship estimates more biased, even though citizenship is a targeted characteristic.

These consistency issues are potentially present in the existing survey weights as well. If noncitizens were overrepresented among nonrespondents within race, Hispanic-origin, age, and gender cells, then the usual survey estimates of citizenship would also be biased.

There was no statistical difference between the 2020 production-weighted estimate (20.1 million) and the 2020 entropy-balance-weighted estimate (20.2 million) of the noncitizen population. However, this represents a decline of only 0.1 million in the entropy-balance-weighted estimate between 2019 and 2020, compared with a decline of 1.6 million in the production-weighted estimate between 2019 and 2020. It is unclear whether the 2019 production-weighted or entropy-balance-weighted level estimate is closer to truth. Nevertheless, the entropy balance weights likely reduce bias in the estimate of the 2019-to-2020 change of the noncitizen population because they adjust for the change in nonresponse between 2019 and 2020, and they adjust late self-responders' weights equivalently in both 2019 and 2020.

[35] Refer to Brown et al. (2018) for a more detailed discussion of data quality issues with survey-based and administrative-data-based citizenship measures.

Figure 13: Number of Noncitizens (2012-2020)



Source: U.S. Census Bureau, 2012 through 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Note: Entropy balance weights were only produced for 2019 and 2020.

6.2.2 Marital Status

While no physical constraints necessarily prevent marital status from changing quickly, in practice it has historically tended to vary slowly, since marital status is relatively persistent for each person and flows between marital states are small relative to their stocks. Between 2016 and 2019, the proportion of people over age 15 who were married changed by no more than 0.3 percentage points year-over-year. However, between 2019 and 2020 that percentage jumped by 1.3 points, a change four times larger than the previous maximum. This is consistent with the positive selection into response by socioeconomic status in 2020 observed in other characteristics. Reweighting for nonresponse reverses this change, turning that 1.3-point jump into a 0.6-point drop. Reweighting similarly changes the observed, unadjusted 0.3-point drop in the never-married share into a 0.5-point increase.

These changes remain large relative to the historical trend; in the case of the never-married share, the change is even larger after reweighting. However, there may be some reasons to expect that the EBW has at least the direction right. Many planned marriages were postponed due to COVID-19 and its associated restrictions. One annual wedding industry report based on a convenience sample estimated that 15 percent of weddings originally planned for March-December 2020 were postponed to 2021 or later.[36] Two

[36] *The Knot 2020 Real Weddings COVID Study*, https://www.wedinsights.com/report/covid-the-knot-real-weddings, accessed 10/12/21.

additional studies drawing on publicly available marriage counts from several states and counties (Manning and Payne, 2021; Wagner, Choi, and Cohen, 2020), found substantial declines in marriage counts in every area studied.

Although similarly affected by changing patterns of survey response, the CPS also measures marital status. While the marital-status universe is smaller, at ages 18 and up, its "married, spouse present" concept is roughly similar to the ACS's "now married (except separated)." Between the 2019 and 2020 CPS ASEC reference years, this category's count shrank 1.6 percent. This compares less favorably to the ACS increasing 3.4 percent using the standard survey weights than it does to the 0.7 percent decrease yielded from the entropy balance weights.

A quick comparison of flows to stocks may provide a useful, back-of-the-envelope bound on potential changes in these shares, particularly the proportion never married. Flows into the never-married pool are mostly young people aging into the universe, while first-time marriages account for most flows out. Deaths and migration are relatively small relative to these two main flows. The 2020 population projections indicated that about 4.2 million 14-year-olds aged into the ACS marital-status universe annually in this period. Therefore, the number of first-time marriages would have needed to decline by about 35 percent to reflect the 0.5-point jump in the never-married share estimated from the entropy balance weights, but they would have needed to have *increased* by 34 percent to rationalize the 0.3-point drop in the standard survey-weighted estimates.

6.2.3 Educational Attainment

As with other stable measures, flows between levels of educational attainment among adults tend to be small relative to their shares of the general population. The proportion of adults aged 25 years and over without a high-school degree changed by no more than a half-percentage point over the 2016-2019 ACS, but it sharply dropped by more than a whole point between 2019 and 2020. Similarly, the share with at least a college degree varied by no more than 0.7 points between 2016 and 2019, but it jumped by 2.3 points between 2019 and 2020. Both of these sudden changes are consistent with the positive selection by socioeconomic status seen in other measures.

EBW shifts the 2020 education distribution downward: those with any college degree are down-weighted while those with no college degree are up-weighted. This is consistent with the 2020 income results, which show the EBW shifting weight away from high-income households toward low-income households. This pattern stands in stark contrast, however, to the effect of reweighting in 2019, which shifts weights in the opposite direction, toward the upper end of the distribution of educational attainment, just as it shifts toward the upper end of the income distribution. The effects of reweighting on the 2019 and 2020 estimates combine to reduce the year-over-year change in these measures, bringing them more in line with analysts' priors and evidence from external sources, such as the National Student Clearinghouse, which show relatively muted trends in educational attainment (Huie et al., 2021).

One particularly relevant source of benchmarks is the CPS. Although the CPS is similar to the ACS in that it is a large, Census-Bureau-fielded household survey facing similar operational challenges during the pandemic, it is also an order of magnitude smaller and conducted much more via interactions with interviewers rather than via mail and Internet modes. Scanniello (2007) investigates differences in education estimates between the 2004 ACS and CPS, finding that the CPS educational attainment distribution was one or two percentage points higher than the ACS across a wide variety of groups, potentially due to the different ways that the questions are worded and the surveys fielded. Rothbaum and Bee (2021) apply EBW to the CPS for survey years 2017 to 2020, finding that while in earlier years reweighting had no statistically significant impact on education distributions, in 2020 the EBW shifted

CPS weights away from college graduates and toward those without a college degree, in a manner similar to EBW's effects on ACS estimates.

6.3 Income and Poverty

Next, we evaluate how the entropy balance weights affect estimates of income and poverty. Appendix Tables 5 and 6 show estimated adjusted gross income and W-2 earnings at the address level using the base weights for all occupied units and the survey and entropy-balance weights for respondents. For average adjusted gross income and W-2 earnings, the survey-weighted and base-weighted estimates are not statistically different in 2019. However, in 2020 the survey-weighted estimate is 6.6 percent higher for adjusted gross income and 5.9 percent higher for W-2 earnings.[37] Because administrative income is a strong predictor of survey income,[38] we can expect survey income estimates to differ substantially when using the regular survey weights vs. the entropy balance weights.

Table 3 and Figure 14 show that difference. With the EBW, median household income is 1.3 percent higher than the survey-weighted estimate in 2019. However, median household income is 3.8 percent lower with the experimental weights in 2020. Instead of the survey-weighted 5.5 percent estimated growth in median household income from 2019 to 2020, the EBW estimate is that median household income increased a small amount, 0.2 percent. Figure 14 shows that this held across the income distribution – estimates using the EBW are close to zero and substantially lower at every percentile of the income distribution than estimates with the regular survey weights.

Table 3 and Appendix Tables 7 to 10 show how estimates of income differed at the state level as well, across the income distribution. For median household income, 36 of the 51 states and DC (71 percent) had lower growth in median household income using the entropy balance weights.[39]

Likewise, poverty (shown in Table 4) was slightly lower using the entropy balance weights in 2019 (12.14 vs. 12.34 percent). However, poverty was about 0.6 percentage points higher in 2020 with the entropy balance weights. Therefore, instead of declining by nearly a full percentage point using the survey weights, with the entropy balance weights poverty declined 0.2 percentage points (from 12.14 in 2019 to 11.94 percent in 2020). At the state level, poverty decreased by less (or increased by more) in 28 states between 2019 and 2020, using the entropy balance weights (shown in column (9) of Table 5). In no state was there a year-to-year change in poverty that was more negative using the entropy balance weights (i.e., a larger decline or a smaller increase).

[37] The 6.6 and 5.9 percent estimates are not statistically different from each other.
[38] Refer to Bollinger (1998) for a visual representation of how well administrative earnings predict survey earnings that is not as affected by random noise in survey responses as statistics like the correlation coefficient are affected.
[39] The point estimate of growth in median household income was lower in all states except Kansas using the entropy balance weights. In no state was the estimate statistically significantly higher using the entropy balance weights.

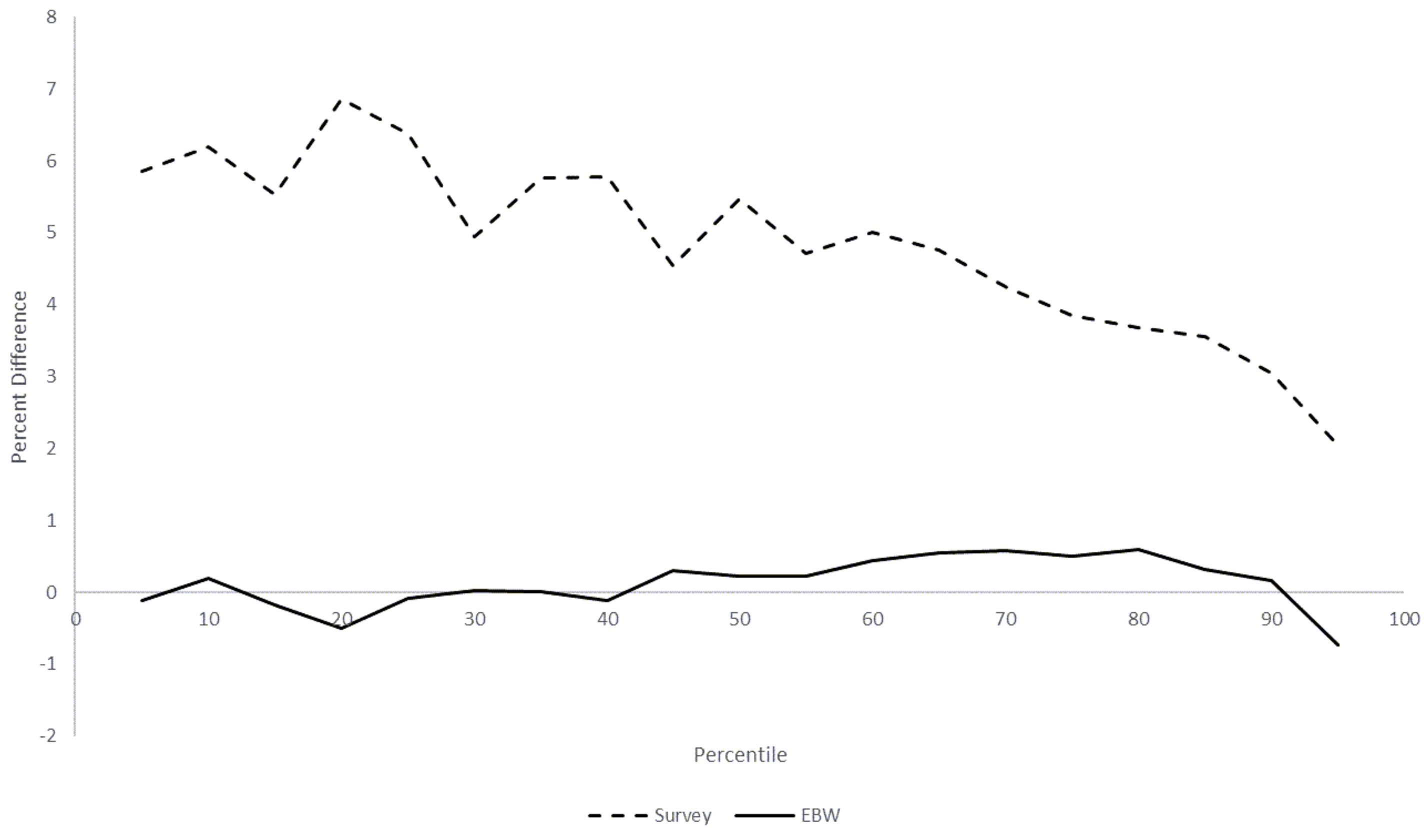
Table 3: Real Median Household Income by State

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	66,360	69,990	67,190	67,340	1.25***	-3.79***	5.47***	0.22**	-5.25***
State									
Alabama	52,310	56,620	52,910	53,960	1.14	-4.70***	8.24***	1.98*	-6.25***
Alaska	76,380	80,300	76,900	80,200	0.68	-0.13	5.13	4.29**	-0.84
Arizona	62,500	67,250	63,610	64,780	1.77***	-3.68***	7.60***	1.84**	-5.76***
Arkansas	49,550	53,780	50,140	51,180	1.19	-4.84***	8.54***	2.07**	-6.46***
California	81,050	85,670	82,540	83,060	1.85***	-3.05***	5.70***	0.63*	-5.07***
Colorado	77,890	79,980	77,820	77,670	-0.09	-2.88***	2.68**	-0.19	-2.88*
Connecticut	79,830	81,740	81,540	79,720	2.15**	-2.47**	2.39*	-2.23**	-4.62***
Delaware	70,940	72,800	72,340	70,910	1.98	-2.60	2.62	-1.98	-4.60
District of Columbia	93,430	97,760	96,590	96,760	3.39*	-1.03	4.63	0.18	-4.46
Florida	59,950	62,560	61,740	61,740	2.99***	-1.31**	4.35***	Z	-4.35***
Georgia	62,470	66,380	62,960	62,840	0.77	-5.32***	6.26***	-0.19	-6.45***
Hawaii	84,040	87,080	86,500	86,390	2.93*	-0.79	3.62	-0.13	-3.74
Idaho	61,370	64,560	60,200	62,770	-1.91	-2.77	5.20**	4.27***	-0.93
Illinois	69,980	72,330	70,670	71,240	0.99**	-1.51***	3.36***	0.81**	-2.55***
Indiana	58,230	62,350	59,680	60,810	2.49***	-2.47***	7.08***	1.89***	-5.18***
Iowa	62,320	64,570	62,130	62,210	-0.30	-3.65***	3.61**	0.13	-3.48**
Kansas	62,610	62,920	62,450	63,320	-0.24	0.64	0.50	1.39	0.90
Kentucky	52,990	56,140	53,890	54,190	1.71*	-3.47***	5.94***	0.56	-5.39***
Louisiana	51,510	55,390	53,160	51,730	3.20***	-6.61***	7.53***	-2.69***	-10.22***
Maine	59,770	61,230	59,840	58,780	0.12	-4.00**	2.44	-1.77	-4.21
Maryland	87,700	92,740	87,960	88,740	0.29	-4.32***	5.75***	0.89	-4.86***
Massachusetts	86,690	89,520	87,310	87,330	0.72	-2.44**	3.26**	0.02	-3.24**
Michigan	60,240	63,080	60,720	61,500	0.79**	-2.50***	4.71***	1.28***	-3.43***
Minnesota	75,400	78,700	75,530	75,520	0.18	-4.04***	4.38***	-0.01	-4.39***
Mississippi	46,230	49,670	46,980	47,250	1.62	-4.89***	7.44***	0.57	-6.87***
Missouri	58,080	60,730	58,210	58,840	0.22	-3.12***	4.56***	1.08	-3.48**
Montana	57,840	59,760	57,400	57,210	-0.76	-4.26**	3.32	-0.33	-3.65
Nebraska	64,040	65,650	63,870	64,590	-0.25	-1.62	2.51*	1.13	-1.39
Nevada	63,960	65,980	63,980	64,570	0.02	-2.12	3.16*	0.92	-2.24
New Hampshire	78,810	81,950	80,280	80,970	1.87	-1.19	3.98*	0.86	-3.12
New Jersey	86,660	89,540	88,410	87,020	2.02***	-2.82***	3.32***	-1.57***	-4.90***
New Mexico	52,450	56,070	52,560	52,060	0.20	-7.16***	6.90***	-0.95	-7.85***
New York	72,890	75,400	74,890	73,400	2.74***	-2.65***	3.44***	-1.99***	-5.43***
North Carolina	57,920	61,210	58,470	59,580	0.96	-2.66***	5.68***	1.90**	-3.78***
North Dakota	65,180	65,570	65,790	61,990	0.92	-5.46***	0.60	-5.78***	-6.37
Ohio	59,340	62,250	59,750	60,340	0.70	-3.08***	4.90***	0.99*	-3.92***
Oklahoma	55,100	57,610	55,590	54,540	0.90	-5.34***	4.56***	-1.89***	-6.44***
Oregon	67,800	71,760	67,980	67,930	0.26	-5.34***	5.84***	-0.07	-5.91***
Pennsylvania	64,250	67,630	64,260	64,910	0.02	-4.02***	5.26***	1.01**	-4.25***
Rhode Island	71,820	77,150	74,090	75,680	3.16**	-1.91	7.42**	2.15	-5.28
South Carolina	56,860	59,490	57,050	56,970	0.33	-4.23***	4.63***	-0.14	-4.77***
South Dakota	60,170	62,160	60,320	60,640	0.25	-2.44*	3.31	0.53	-2.78
Tennessee	56,630	59,540	57,410	56,950	1.38**	-4.35***	5.14***	-0.80	-5.94***
Texas	64,860	68,840	66,350	66,030	2.30***	-4.08***	6.14***	-0.48	-6.62***
Utah	76,530	80,270	76,830	77,830	0.39	-3.04***	4.89***	1.30	-3.59**
Vermont	63,780	70,310	65,010	67,430	1.94	-4.10**	10.24***	3.72*	-6.52*
Virginia	77,250	81,340	77,710	79,220	0.60	-2.61***	5.29***	1.94**	-3.35***
Washington	79,670	82,280	79,690	80,410	0.02	-2.27***	3.28***	0.90	-2.37*
West Virginia	49,410	50,630	49,450	49,400	0.07	-2.44*	2.47	-0.10	-2.57
Wisconsin	65,000	66,730	65,160	64,870	0.26	-2.80***	2.66***	-0.45	-3.11***
Wyoming	66,060	70,440	66,910	66,430	1.29	-5.68***	6.63**	-0.72	-7.35**

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Notes: This table shows real median household income (in 2020 dollars, adjusted by the CPI-U-RS) by state. Columns (1) and (2) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy balance weights. Columns (5) and (6) show the percent difference each year between the production and entropy balance weights. Columns (7) and (8) show the year-to-year estimates for the production and entropy balance weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates an estimate rounds to zero (< 0.005 for percent differences).

Figure 14: Year-to-Year Change in Real Household Income Across the Distribution, Survey vs. EBW



Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](census.gov).

Notes: This figure shows estimates of the change in real household income (adjusted by the CPI-U-RS) using the survey and experimental entropy balance weights at each 5th percentile from the 5th to 95th. All estimates are linear interpolations across bins of $2,500.

Table 4: Poverty Rate by Age

Poverty	2019 Survey (1)	2019 EBW (2)	2020 Survey (3)	2020 EBW (4)	Difference (EBW-Survey) 2019 (5)	Difference (EBW-Survey) 2020 (6)	Year-to-Year Change Survey (7)	Year-to-Year Change EBW (8)	Diff-in-Diff (9)
Overall	12.34	12.14	11.38	11.94	-0.20***	0.56***	-0.96***	-0.20***	0.76***
Under 18 years	16.75	16.31	15.04	15.69	-0.44***	0.65***	-1.71***	-0.61***	1.10***
18 to 64 years	11.50	11.36	10.68	11.22	-0.14***	0.55***	-0.82***	-0.14***	0.68***
65 years and over	9.45	9.35	9.08	9.57	-0.10**	0.49***	-0.36***	0.22***	0.59***

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Notes: This table shows poverty rates by age using the survey and entropy balance weights. Columns (1) and (3) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (2) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy balance weights. Columns (5) and (6) show the percentage-point difference each year between the production and entropy balance weights. Columns (7) and (8) show the year-to-year estimates for the production and entropy balance weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons.

Table 5: Poverty Rate by State

	2019		2020		Difference (EBW-Survey)		Year-to-Year Change		Diff-in-Diff
	Survey	EBW	Survey	EBW	2019	2020	Survey	EBW	
Poverty	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	12.34	12.14	11.38	11.94	-0.20***	0.56***	-0.96***	-0.20***	0.76***
State									
Alabama	15.46	15.52	13.52	14.68	0.06	1.16***	-1.94***	-0.83***	1.11**
Alaska	10.08	10.12	9.30	9.15	0.04	-0.15	-0.78	-0.96***	-0.18
Arizona	13.47	13.13	12.44	12.79	-0.34	0.35	-1.03**	-0.34***	0.69
Arkansas	16.21	16.45	13.82	15.33	0.24	1.51***	-2.38***	-1.12***	1.27**
California	11.75	11.59	10.85	11.43	-0.16	0.58***	-0.91***	-0.17***	0.74***
Colorado	9.35	9.30	8.64	8.96	-0.05	0.32	-0.71**	-0.34***	0.37
Connecticut	10.03	9.98	9.48	9.81	-0.05	0.33	-0.56	-0.18	0.38
Delaware	11.26	10.81	11.17	11.27	-0.45	0.10	-0.09	0.46	0.55
District of Columbia	13.45	13.32	13.42	14.79	-0.14	1.37*	-0.03	1.47***	1.51
Florida	12.66	12.46	11.94	12.25	-0.20	0.31	-0.72***	-0.21***	0.51**
Georgia	13.30	13.41	12.44	13.86	0.11	1.43***	-0.86**	0.46***	1.31***
Hawaii	9.33	8.70	8.97	8.92	-0.63	-0.05	-0.37	0.22	0.58
Idaho	11.17	11.01	10.02	10.07	-0.17	0.05	-1.16*	-0.94***	0.22
Illinois	11.48	11.08	10.48	11.01	-0.40**	0.52***	-1.00***	-0.08	0.92***
Indiana	11.90	12.03	11.15	11.73	0.13	0.57**	-0.75**	-0.31***	0.44
Iowa	11.17	10.75	9.99	10.43	-0.41	0.44	-1.18***	-0.33**	0.85**
Kansas	11.43	11.48	10.52	10.83	0.04	0.31	-0.91*	-0.65***	0.27
Kentucky	16.26	15.59	14.11	14.84	-0.67**	0.74**	-2.16***	-0.75***	1.41***
Louisiana	19.00	18.51	16.98	17.77	-0.49	0.79*	-2.01***	-0.74***	1.28**
Maine	10.87	11.04	10.05	10.65	0.17	0.60	-0.82	-0.39*	0.43
Maryland	9.02	8.99	8.01	8.77	-0.03	0.76***	-1.02***	-0.23**	0.79**
Massachusetts	9.40	9.49	9.06	9.42	0.09	0.37	-0.35	-0.06	0.28
Michigan	12.99	12.72	12.18	12.70	-0.26	0.52***	-0.81***	-0.03	0.79***
Minnesota	8.97	8.65	8.02	8.26	-0.32	0.24	-0.95***	-0.39***	0.56**
Mississippi	19.60	19.89	18.31	18.75	0.28	0.44	-1.29*	-1.14***	0.16
Missouri	12.94	12.61	11.33	12.12	-0.33	0.79***	-1.60***	-0.49***	1.12***
Montana	12.65	12.19	12.21	12.98	-0.45	0.77	-0.44	0.79***	1.23*
Nebraska	9.89	9.88	8.79	9.00	-0.01	0.21	-1.10**	-0.88***	0.22
Nevada	12.50	12.36	12.09	12.35	-0.14	0.26	-0.41	-0.01	0.39
New Hampshire	7.27	7.00	6.60	6.99	-0.27	0.39	-0.67	-0.01	0.66
New Jersey	9.16	8.96	9.14	9.55	-0.20	0.40*	-0.02	0.59***	0.61*
New Mexico	18.18	17.57	16.80	17.80	-0.60	1.00*	-1.37**	0.23	1.60***
New York	13.03	12.59	12.45	12.69	-0.44***	0.25	-0.58**	0.11*	0.69***
North Carolina	13.59	13.49	12.40	13.01	-0.10	0.61**	-1.19***	-0.48***	0.70**
North Dakota	10.57	10.40	10.32	11.03	-0.17	0.72	-0.26	0.63	0.89
Ohio	13.07	12.92	12.03	12.65	-0.15	0.62***	-1.04***	-0.27***	0.77***
Oklahoma	15.18	15.06	13.26	14.42	-0.11	1.16***	-1.92***	-0.64***	1.28***
Oregon	11.38	11.18	10.35	10.95	-0.20	0.61*	-1.03**	-0.23*	0.80**
Pennsylvania	12.02	11.82	10.44	10.86	-0.20	0.42**	-1.58***	-0.96***	0.63**
Rhode Island	10.82	10.38	9.40	9.65	-0.44	0.25	-1.43*	-0.73**	0.69
South Carolina	13.85	13.77	12.99	13.98	-0.08	0.99***	-0.86*	0.21	1.07**
South Dakota	11.93	11.60	12.58	11.66	-0.33	-0.91*	0.65	0.06	-0.59
Tennessee	13.85	13.85	12.70	13.69	-0.01	0.99***	-1.15***	-0.16	0.99***
Texas	13.63	13.19	12.74	13.46	-0.44***	0.72***	-0.89***	0.27***	1.16***
Utah	8.91	8.54	7.66	7.12	-0.36	-0.54	-1.25***	-1.42***	-0.18
Vermont	10.17	9.51	8.84	9.57	-0.66	0.73	-1.33**	0.06	1.39**
Virginia	9.94	9.87	8.77	9.16	-0.07	0.39*	-1.17***	-0.71***	0.46*
Washington	9.78	9.68	8.91	9.52	-0.10	0.60**	-0.86***	-0.16*	0.70**
West Virginia	16.03	16.09	15.80	16.17	0.06	0.37	-0.23	0.07	0.30
Wisconsin	10.42	10.31	9.69	10.06	-0.11	0.37*	-0.73**	-0.25***	0.48
Wyoming	10.11	10.37	9.21	9.27	0.26	0.06	-0.90	-1.10***	-0.21

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Notes: This table shows poverty rates by state. Columns (1) and (3) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (2) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy balance weights. Columns (5) and (6) show the percent difference each year between the production and entropy balance weights. Columns (7) and (8) show the year-to-year estimates for the production and entropy balance weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons.

6.4 Labor Force and Employment Characteristics

Labor force and employment characteristics demonstrated suspicious patterns when using the 2020 1-year production weights. Due to pandemic-related stay-at-home orders, as well as other pandemic-related economic challenges in 2020, a marked increase in the unemployment rate was expected in the 2020 ACS data. However, although the unemployment rate did increase between 2019 and 2020 when using the 2020 1-year production weights, the magnitude of change did not track well with a trusted external benchmark.

For the last decade the ACS consistently followed the trend of the official published Bureau of Labor Statistics (BLS) average annual unemployment rate estimates. Specifically, from 2010 to 2019, the published ACS unemployment rate was consistently between 0.8 percentage points and 1.4 percentage points higher than the BLS unemployment rate.[40] However, this decade-long trend markedly changed in 2020: the BLS unemployment rate was 1.6 percentage points higher than the 2020 1-year production weighted ACS unemployment estimate. The BLS annual average unemployment rate for the U.S. in 2020 was 8.1 percent, an increase of 4.4 percentage points from the official 3.7 percent 2019 BLS estimate (BLS, 2021). Conversely, the ACS unemployment rate using 2020 1-year production weights was 6.5 percent, a 2-percentage-point increase from the 2019 ACS production estimate of 4.5 percent.

Civilian labor force participation also did not match expectations using the 2020 1-year production weights. Specifically, estimates of civilian labor force participation using 2020 ACS 1-year production weights decreased from 63.4 percent in 2019 to 62.6 percent in 2020, a 0.8-percentage-point decrease. On the other hand, the BLS civilian labor force participation rate decreased by 1.4 percentage points, from 63.1 percent in 2019 to 61.7 percent in 2020 (BLS, 2021). Although civilian labor force participation rates using 2020 ACS 1-year production weights did move in the expected direction, the magnitude of change was less than expected.

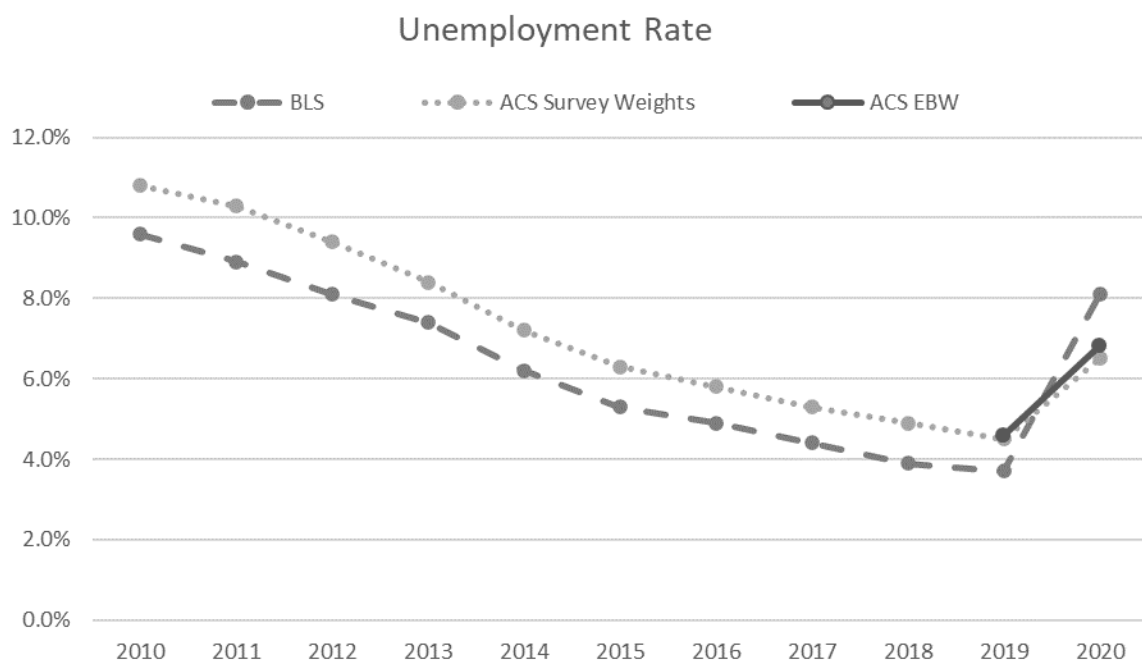
We expect the entropy balance weights to improve the quality of the 2020 ACS 1-year estimates and produce an unemployment rate and civilian labor force participation rate that are closer to the 2020 BLS estimates. The balance constraints included moment conditions directly related to employment, including receipt of W-2s, receipt of multiple W-2s that might indicate a job change, summary information on earnings differences between the survey year and prior year, earnings amounts, and receipt of Form 1099-G, which can indicate receipt of government-sponsored unemployment insurance.

Results indicate that the 2020 ACS unemployment rate increased from 6.5 percent when using the ACS production weights to 6.8 percent when using the entropy balance weights. Furthermore, the civilian labor force participation rate decreased from 62.6 percent when using the 2020 ACS 1-year production weights to 62.2 percent when using the 2020 entropy balance weights. Although the unemployment rate and the civilian labor force participation rate significantly changed in the expected direction when using the entropy balance weights, the magnitude of the change is not large enough to close the gap between the BLS and the ACS estimates of unemployment and civilian labor force participation. This suggests that data quality issues may still be present in the ACS employment data even when using the entropy balance weights. It is possible that the ACS and BLS employment questions were differentially sensitive to pandemic-specific employment changes, which could result in divergent estimates of unemployment and civilian labor force participation. Alternatively, the annual frequency of the administrative records that we

[40] For a comparison of ACS and BLS question wording, methodology, and unemployment rate estimates from 2007 to 2009, refer to Kromer and Howard (2011).

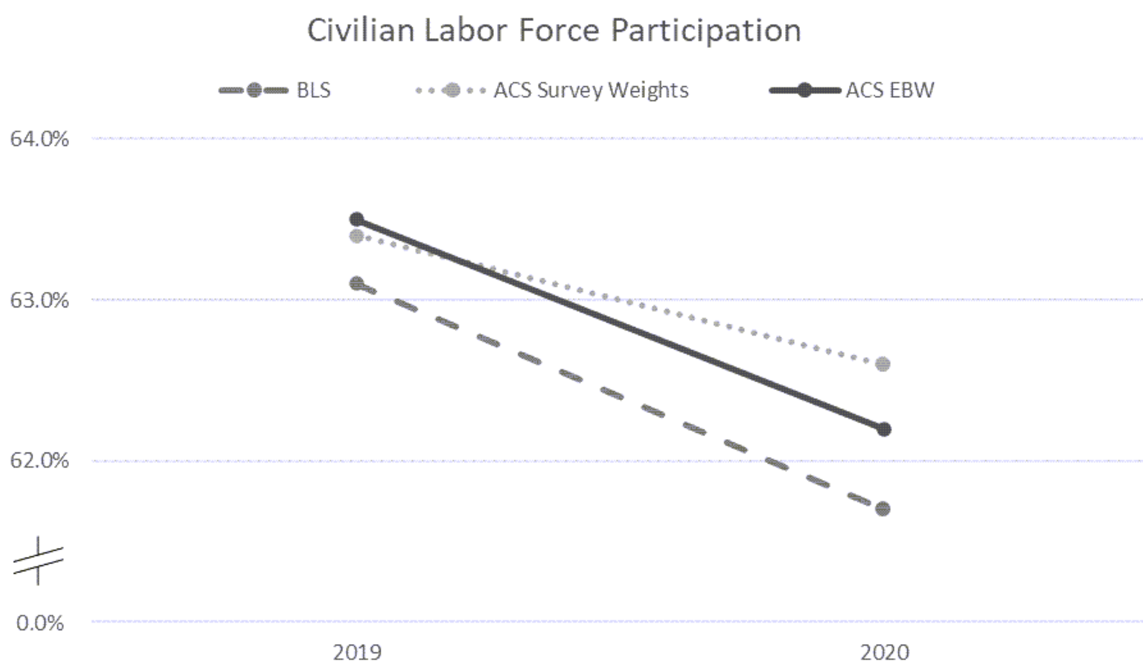
use to adjust for nonresponse may have been too coarse to capture the large subannual changes in employment statistics adequately, resulting in nonresponse bias in within-year employment changes.

Figure 15: Unemployment Rate from 2010 to 2020



Source: U.S. Census Bureau, 2010 through 2020 American Community Survey 1-year data and Bureau of Labor Statistics (2021) "Employment status of the civilian noninstitutional population, 1950s to date." https://www.bls.gov/cps/tables.htm#annual. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Note: Entropy balance weights were only produced for 2019 and 2020.

Figure 16: Civilian Labor Force Participation in 2019 and 2020



Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data and Bureau of Labor Statistics (2021) "Employment status of the civilian noninstitutional population, 1950s to date." https://www.bls.gov/cps/tables.htm#annual. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Note: Civilian labor force participation is labor force participation among civilians.

6.5 Medicaid Coverage

Yet another set of measures exhibiting anomalously large swings are those characterizing health insurance coverage. While it would not be unreasonable to expect a pandemic and associated economic disruption to have large, direct impacts on Americans' health insurance coverage, the changes observed in the ACS do not align well with those observed in external benchmarks. In particular, while private insurance is difficult to benchmark, and Medicare coverage is nearly collinear with eligibility at age 65, Medicaid is one of the largest federal programs covering low-income adults. Thus, Medicaid enrollment may be expected to be highly correlated with the overall nonresponse relationships observed in other variables and easily benchmarked from administrative records. The Centers for Medicare and Medicaid Studies (CMS) have annually tabulated the number of people covered by Medicaid, and changes in these counts have closely corresponded to changes in estimates from the ACS. However, between 2019 and 2020 ACS showed a net decline in Medicaid coverage by 2.4 million people. Counts from CMS, by contrast, said that Medicaid covered an additional 9.8 million people on net, between February 2020 and January 2021, and an additional 3.8 million people on net, comparing averages of the 12 months from the

2019 and 2020 monthly reports.[41] Reweighting using EBW slightly down-weighted ACS Medicaid recipients in 2019 but strongly up-weighted ACS Medicaid recipients in 2020. Specifically, EBW shifted the count of individuals covered by Medicaid in 2019 down to 62.5 million (standard error 40,210) from 63.2 million according to the standard weight, while EBW shifted the analogous count for 2020 up to 63.6 million (standard error 49,290) from 60.8 million according to the standard weight.[42] This resulted in a net increase of 1.1 million covered persons between 2019 and 2020 according to the EBW weights.

[41] Center for Medicare and Medicaid Services, February 2021 Medicaid and CHIP Enrollment Trends Snapshot, Appendix A <https://www.medicaid.gov/medicaid/national-medicaid-chip-program-information/downloads/february-2021-medicaid-chip-enrollment-trend-snapshot.pdf>. 2019 and 2020 ACS 1-year estimates are averages of the 12 months from each year.

[42] The universe for these calculations is all persons in households. For ease of comparison, this is the same universe for Medicaid calculations that was used in U.S. Census Bureau (2021).

7. Conclusion

The COVID-19 pandemic introduced myriad disruptions to the fielding of the American Community Survey. Despite the Census Bureau's attempts to address these disruptions, ultimately the representativeness of the households that responded to the survey fell short of Census Bureau quality standards. Consequently, estimates of various characteristics such as marital status, educational attainment, building structure type, the noncitizen population, and Medicaid coverage displayed unexpected trends or disagreed substantially with external benchmarks.

We propose a method of adjusting respondents' weights to improve the utility of the 2020 ACS data. This method uses linked data from Census Bureau data collections, government agencies, and third-party organizations that we observe for both respondents and nonrespondents of the survey. The linked data cover a variety of topics, including demographics, household structure, income, employment, financial holdings, and household characteristics. We use these linked data to document that ACS respondents became less representative of the overall sample along multiple dimensions. While the April, May, and June panels suffered the greatest decline in representativeness, the respondent sample settled at a level less representative of the overall sample relative to 2019 even after data collection procedures had mostly returned to normal.

In light of this less representative respondent sample, we use entropy balancing to adjust respondents' weights to be more representative of the overall sample according to the linked decennial census, administrative, and third-party data. Entropy balancing has numerous advantages in this context, including its flexibility, statistical efficiency, computational efficiency, and ability to ensure that reweighted moments calculated on respondents match full-sample moments. We applied this reweighting algorithm to both 2019 and 2020 ACS data to allow for valid comparisons of weighted data across years and to evaluate the new weights' performance in a year with a more typical nonresponse pattern.

We believe these experimental entropy balance weights have significantly improved the utility of the 2020 ACS data, and will allow the ACS to remain a useful source for studying the U.S. population during this eventful period. The entropy balance weights appear to improve estimates for a variety of topics, including income, employment, housing characteristics, marital status, educational attainment, and Medicaid coverage. Nevertheless, potential data quality issues remain for some topics, such as employment, marital status, educational attainment, and Medicaid coverage. For the sake of transparency, an online appendix offers estimates for both the standard weights and experimental entropy balance weights in both 2019 and 2020, covering a wider variety of topics than discussed in this paper. Additionally, our experimental methodology has not been as thoroughly investigated and tested as the standard weighting practices applied at the Census Bureau. More research is needed into the properties of novel methods that incorporate administrative data into weighting algorithms for Census Bureau surveys.

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Appendix A: Discussion of Changes to CAPI Subsampling Factor

The CAPI subsampling factor was modified for the standard ACS weighting procedures beginning in 2020. In the ACS, the overall goal is to increase the base weights on households sampled in CAPI to account for the fact that some households are not selected for follow-up if they do not respond on their own. However, it is unclear how to treat households that self-respond after the beginning of CAPI operations. These households have historically received their base weight without any CAPI-related adjustments, regardless of whether they were sampled for CAPI or not.[43] The underlying assumption was that late self-responders were equally representative of the population as households with the same base weight that responded on their own prior to the start of CAPI operations. Before the Internet instrument was introduced in 2013, late self-responders made up a small proportion of the sample, so being sampled for nonresponse follow-up did not greatly increase the likelihood of self-responding. However, the number of these late self-responders has grown over time, suggesting a growing scope for any difference in representativeness between self-responders before and after the start of CAPI operations to bias weighted estimates.

For 2020 ACS, an adjustment to the weighting algorithm was planned before the COVID-19 pandemic to scale up the base weight (BW) of households who self-respond after being sampled in CAPI by the subsampling factor (SSF). Additionally, households sampled in CAPI receive a weighting subsampling factor correction (SSFCORR) to have the sum of weights in a geography after all these corrections equal the sum of the base weights at the time of sampling. This correction factor is based on geography and is done separately for respondent-occupied households versus all other types of addresses (e.g., nonrespondents, vacants, group quarters). There was no plan to bridge this change to the CAPI subsampling factor, so 2019 and 2020 ACS data would not have been directly comparable even in the absence of the COVID-19 pandemic

In our work, we make some adjustments to take advantage of some benefits of the EBW algorithm and to make our final weighted sample comparable between 2020 and earlier ACS years. One valuable feature of the EBW program is that for our administrative-data-based moments (e.g., percentage of occupied households that have interest income), the weights we use to construct the targets do not have to be the same as the initial base weights we apply to respondents in the weighting algorithm. Therefore, to reduce the sensitivity of our estimate to the treatment of late-self respondents, we do the following for creating our target moments:

1. For households sampled for CAPI, their weights get inflated by the subsampling factor regardless of response mode.
2. For households not sampled for CAPI, their weights always get set to zero, even if they become late self-respondents.
3. For 2020, we do not apply the new subsampling factor correction.

This procedure offers a longitudinally consistent way of constructing a sample of occupied households that should be less subject to self-selected response, thereby improving the accuracy of our administrative-data-based moments.

Next, for respondents' q_i weights in (1) that are a starting place for the entropy balancing algorithm, we do the following:

[43] Refer to https://www2.census.gov/programs-surveys/acs/methodology/design_and_methodology/acs_design_methodology_ch11_2014.pdf for a detailed discussion of the prior approach.

1. For households sampled for CAPI in any year, their weights get inflated by the subsampling factor regardless of response mode. This differs from the standard weighting methodology for years prior to 2020, but it improves the comparability of experimental estimates over time.
2. For households not sampled for CAPI, keep the base weight if they become late self-respondents. This is the same as the standard weighting methodology for all ACS years.
3. For 2020, we do apply the new subsampling factor correction to keep the sum of corrected weights in a geography equal to the sum of base weights. For years prior to 2020, we do not apply the new subsampling factor correction because this factor has only been constructed for 2020 ACS.[44] However, this correction has a relatively small effect on the final adjusted base weights, given that the mean value of this variable for affected households is 95.76 percent. Therefore, not having this factor in earlier ACS years should have minimal effect on the comparability of our experimental estimates over time.

To help summarize all the details related to adjusting the base weights to account for CAPI subsampling, the following tables describe the prior ACS procedure for adjusting base weights (Appendix Table 1), the change for 2020 planned prior to the COVID-19 pandemic (Appendix Table 2), our procedure for adjusting the base weight to construct administrative data moments (Appendix Table 3), and the procedure we use for adjusting the base weights of respondents to create the q_i inputs to the EBW algorithm (Appendix Table 4). Cells in Appendix Tables 2-4 that are different from Appendix Table 1 are colored in red.

[44] Data for the 2020 ACS come from November 2019 to December 2020 panel months.

Appendix Table 1: Base Weights Adjustment in ACS Prior to 2020

	Respond Before CAPI	Sampled for CAPI			Not Sampled For CAPI	
	Self-Response	Late Self-Response	Interviewer-Administered Response	Nonrespondent	Late Self-Response	Nonrespondent
Set Weights to Zero?	No	No	No	No	No	Yes
Apply CAPI Subsampling Factor (SSF)?	No	No	Yes	Yes	No	N/A
Weights After Adjustments	BW	BW	BW*SSF	BW*SSF	BW	0

Appendix Table 2: Base Weights Adjustment in ACS Planned for 2020 Prior to COVID-19 Pandemic

	Respond Before CAPI	Sampled for CAPI			Not Sampled For CAPI	
	Self-Response	Late Self-Response	Interviewer-Administered Response	Nonrespondent	Late Self-Response	Nonrespondent
Set Weights to Zero?	No	No	No	No	No	Yes
Apply CAPI Subsampling Factor (SSF)?	No	Yes	Yes	Yes	No	N/A
Apply Subsampling Correction (SSFCORR)	No	Yes	Yes	Yes	No	N/A
Weights After Adjustments	BW	BW*SSF* SSFCORR	BW*SSF* SSFCORR	BW*SSF* SSFCORR	BW	0

Appendix Table 3: Base Weights Adjustment for Experimental Entropy Balance Weights-Constructing Administrative Data Target Moments

	Respond Before CAPI	Sampled for CAPI			Not Sampled For CAPI	
	Self-Response	Late Self-Response	Interviewer-Administered Response	Nonrespondent	Late Self-Response	Nonrespondent
Set Weights to Zero?	No	No	No	No	Yes	Yes
Apply CAPI Subsampling Factor (SSF)?	No	Yes	Yes	Yes	N/A	N/A
Apply Subsampling Correction (SSFCORR)?	No	No	No	No	N/A	N/A
Weights After Adjustments	BW	BW*SSF	BW*SSF	BW*SSF	0	0

Appendix Table 4: Base Weights Adjustment for Experimental Entropy Balance Weights-Weights Used as a Starting Point of Respondents

	Respond Before CAPI	Sampled for CAPI			Not Sampled For CAPI	
	Self-Response	Late Self-Response	Interviewer-Administered Response	Nonrespondent	Late Self-Response	Nonrespondent
Set Weights to Zero?	No	No	No	No	No	Yes
Apply CAPI Subsampling Factor (SSF)?	No	Yes	Yes	Yes	No	N/A
Apply Subsampling Correction (SSFCORR) for 2020?	No	Yes	Yes	Yes	No	N/A
Weights After Adjustments: 2020	BW	BW*SSF*SSFCORR	BW*SSF*SSFCORR	BW*SSF*SSFCORR	BW	0
Weights After Adjustments: Before 2020	BW	BW*SSF	BW*SSF	BW*SSF	BW	0

Appendix B: More Details on the Weighting Model

First, we provide more detail about the variables used in the different weighting models.

1. Housing-unit level weights
   - Linkage indicators
     - Any administrative data set
     - Information returns
       - All forms noted in Figure 1
       - SSA-1099 by age (<60, ≥60)
     - Black Knight information on the characteristics of the housing unit
     - Linkage of W-2 jobs to the Business Register
   - Demographics
     - Indicators - for the presence any household member:
       - By race (White, Black, Asian, American Indian or Alaska Native, any other race)
       - Hispanic origin
       - Child
       - Adult male
       - Adult female
       - Foreign born
       - Noncitizen
       - Age bins with cutoffs at 6, 10, 18, 40, and 60
     - Number of individuals
     - Number of adults
     - 1040 filing as married
   - Income
     - 1040 indicators
       - Income – interest, dividends, gross rental income,
       - 1040 filing from year t or $t-1$
       - Indicators for filing of schedules A, C, D, E, and SE
     - Indicators for income in bins with the cutoffs (in thousands of dollars):[45]
       - 25, 50, 75, 100, 150, 200 – W-2 earnings, adjusted gross income, Total Money Income (from 1040 filings)
       - 5, 15, 25, 50 – OASDI benefits and SSI
     - Inverse hyperbolic sine of W-2 earnings, adjusted gross income, assessed property value, OASDI benefits, SSI, (Total Money Income minus Wage and Salary Earnings in 1040 filings)
     - Maximum number of jobs
     - Change in earnings information
       - Indicator for household member that started/stopped working (received W-2 in year t, but not $t-1$ or vice versa)
       - Indicators for arc percent change in earnings between year $t-1$ and year t, $\frac{y_t - y_{t-1}}{\left(\frac{y_t + y_{t-1}}{2}\right)}$ with cutoffs at -0.5, -0.1, 0, 0.1, and 0.5
     - Job characteristics

[45] The bin cutoffs were adjusted for inflation using the CPI-U-RS, with the values shown in 2019 dollars.

            - NAICS sector – 20 different NAICS sector categories (generally at the 2-digit level)
    - Housing characteristics
        - Housing type – single family unit, multi-family unit, and mobile home
        - Assessed property value
            - in bins with cutoffs at 50, 100, 250, and 500 thousand dollars
            - Inverse hyperbolic sine
        - Indicator for owner-occupied unit
    - Interactions
        - (Race and Hispanic origin) by (W-2 earnings bins, adjusted gross income bins, indicators for interest, dividends, and gross rental income, 1099 indicators, 1040 filing as married)
        - Income interactions (of inverse hyperbolic sine of income) – W-2 earnings by adjusted gross income, W-2 earnings by OASDI benefits, and OASDI benefits by adjusted gross income
    - County-level information (for counties with population greater than 65,000 in year t)
        - Income – bins of W-2 earnings and inverse hyperbolic sine of adjusted gross income
        - Change in earnings information – indicator for household member that started/stopped working

2. Person-level weights
    A. Preserve housing-unit level moments – most of the moments in 1, but with reduction in dimensionality if necessary for model convergence
    B. Spousal equivalence
        - Linkage indicators for W-2, 1099 forms, 1040 filings
        - Demographics
        - Income
            - 1040 indicators
                - 1040 filing from year t or $t-1$
                - 1040 tax filing, including indicators for schedules A, C, D, E, and SE
            - Binned W-2 earnings and adjusted gross income
        - Interactions
            - (Race and Hispanic origin) by (1040 filing as married)
    C. External housing and population targets
        - Age – each year, truncated at 85
        - Housing unit count
        - County population
        - Interactions
            - (Age in bins with cutoffs at 6, 13, 18, 25, 35, 45, 55, and 65) by sex by (race and Hispanic origin)
            - Race (White and Black alone or in combination) by Hispanic origin

D. Monthly balancing
   - Income – Binned W-2 earnings and inverse hyperbolic sine of W-2 earnings and adjusted gross income
   - Change in earnings information – indicator for household member that started/stopped working

We also impose a condition that at least 100 observations must have a non-zero value in a variable for that to be included in the weighting model. Otherwise, that moment condition is dropped.

The number of moment conditions in a given state will vary primarily in relation to the number of counties. For example, if a state has 50 counties, then there can be up to 350 county-level W-2 earnings bin moments (50 counties by 7 earnings bin dummies). In practice, the stage 2 model often has more than 1,000 moment conditions, although the number of stage 2 conditions for a state with a small population and/or few counties will be closer to 500.

Appendix C: Additional Tables

Appendix Table 5: Validating Entropy Balance Weights in the 2019 ACS

	Estimates			Validation	Percent Difference			Validation Percent Difference
				2nd Stage Target				
	Base	Survey	EBW	(Average household EBW)	Survey - Base	EBW - Base	EBW - Survey	2nd Stage Target - Base
Characteristic	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adjusted Gross Income								
Average	86,430	86,790	86,120	85,450	0.4	-0.4	-0.8	-1.1
	(998)	(1,007)	(149)	(138)	(0.4)	(1.1)	(1.1)	(1.1)
25th Percentile	2,385	2,460	2,359	2,385	3.1***	-1.1***	-4.1***	Z
	(4)	(6)	(4)	(4)	(0.2)	Z	(0.2)	Z
50th Percentile	48,820	50,000	48,890	48,690	2.4***	0.1***	-2.2***	-0.3***
	(82)	(128)	(88)	(81)	(0.2)	Z	(0.2)	Z
75th Percentile	107,000	108,000	107,700	106,900	0.9***	0.6***	-0.3***	-0.1***
	(104)	(146)	(125)	(108)	(0.1)	Z	(0.1)	Z
90th Percentile	182,500	183,500	183,900	182,300	0.6***	0.8***	0.2**	-0.1
	(240)	(270)	(241)	(212)	(0.1)	(0.1)	(0.1)	(0.1)
W2 Earnings								
Average	64,010	64,270	63,370	63,140	0.4	-1.0	-1.4	-1.4
	(965)	(1,001)	(106)	(99)	(0.4)	(1.4)	(1.5)	(1.4)
50th Percentile	33,030	33,430	32,510	32,920	1.2***	-1.6***	-2.7***	-0.3***
	(79)	(102)	(85)	(74)	(0.3)	(0.1)	(0.3)	(0.1)
75th Percentile	88,880	89,360	89,150	88,740	0.5***	0.3***	-0.2**	-0.2**
	(113)	(130)	(113)	(103)	(0.1)	(0.1)	(0.1)	(0.1)
90th Percentile	154,600	155,000	155,600	154,500	0.2**	0.6***	0.4***	-0.1***
	(210)	(213)	(219)	(198)	(0.1)	Z	(0.1)	Z
In Any Admin Data	86.1	86.8	85.9	86.1	0.8***	-0.3***	-1.1***	Z
	Z	Z	Z	Z	Z	Z	Z	Z
Demographic Characteristics (Any Member Is)								
Asian	5.5	5.6	5.6	5.6	1.4***	0.6***	-0.8**	0.3***
	Z	Z	Z	Z	(0.3)	(0.1)	(0.3)	(0.1)
Black	12.9	13.2	12.3	12.9	2.4***	-4.1***	-6.3***	0.5***
	Z	Z	Z	Z	(0.2)	(0.1)	(0.3)	Z
Other Race	7.6	7.6	7.4	7.6	0.1	-2.6***	-2.8***	0.8***
	Z	Z	Z	Z	(0.3)	(0.1)	(0.4)	(0.1)
Native American or Alaskan Native	1.5	1.6	1.5	1.5	3.3***	-2.0***	-5.1***	0.2
	Z	Z	Z	Z	(0.6)	(0.3)	(0.7)	(0.2)
White	66.3	66.7	66.5	66.2	0.6***	0.3***	-0.3***	-0.2***
	Z	(0.1)	Z	Z	(0.1)	Z	(0.1)	Z
Hispanic	13.0	13.2	12.7	13.1	1.6***	-2.5***	-4.1***	1.0***
	Z	Z	Z	Z	(0.2)	(0.1)	(0.2)	(0.1)
Non-Citizen	11.4	11.5	11.3	11.5	0.9***	-1.2***	-2.1***	0.5***
	Z	Z	Z	Z	(0.3)	(0.1)	(0.3)	(0.1)
Foreign Born	17.8	18.0	17.6	17.9	1.2***	-1.0***	-2.2***	0.3**
	Z	Z	Z	Z	(0.2)	(0.1)	(0.2)	(0.1)
Female	70.8	71.6	70.7	70.9	1.1***	-0.2***	-1.2***	0.2***
	Z	(0.1)	Z	Z	(0.1)	Z	(0.1)	Z
Male	67.2	68.1	67.2	67.2	1.3***	Z	-1.4***	Z
	Z	Z	Z	Z	(0.1)	Z	(0.1)	Z

Source: U.S. Census Bureau, 2019 American Community Survey 1-year data linked to decennial census, administrative, and third-party data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Notes: This table provides information on how well the experimental entropy balance weights and survey weights match estimates of the distribution of income and demographic characteristics in the linked data. Columns (1)-(3) respectively show address-level estimates from linked data using the survey base weights (based on probability of selection into the sample and CAPI subsampling for all occupied units), final survey weights, and entropy balance weights. The estimates in Column (1) are the targets for the entropy balancing procedure. Column (4) shows estimates at the household level using the average weights of the individual members (as shown in Equation (7)), which is the target of the entropy balancing person-level weights in 2.A (refer to Table 1). Columns (5)-(8) show the percent difference between the various estimates in (1)-(4). Percentile estimates are interpolated across bins of $2,500 and include addresses with 0 income. ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates an estimate or standard error rounds to zero (is less than < 0.05) for any percent or percent difference.

Appendix Table 6: Validating Entropy Balance Weights in the 2020 ACS

	Estimates			Validation	Percent Difference			Validation Percent Difference
	Base	Survey	EBW	2nd Stage Target (Average household EBW)	Survey - Base	EBW - Base	EBW - Survey	2nd Stage Target - Base
Characteristic	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adjusted Gross Income								
Average	84,210	89,790	84,240	83,800	6.6***	Z	-6.2***	-0.5
	(424)	(504)	(183)	(168)	(0.6)	(0.5)	(0.5)	(0.5)
25th Percentile	2,302	5,466	2,278	2,301	137.4***	-1.1***	-58.3***	-0.1***
	(4)	(129)	(4)	(4)	(5.5)	(0.1)	(0.9)	Z
50th Percentile	47,540	54,460	47,470	47,480	14.6***	-0.2**	-12.8***	-0.1
	(119)	(127)	(126)	(115)	(0.3)	(0.1)	(0.2)	(0.1)
75th Percentile	106,400	113,300	106,700	106,200	6.6***	0.4***	-5.8***	-0.1
	(159)	(174)	(156)	(146)	(0.1)	(0.1)	(0.1)	(0.1)
90th Percentile	183,300	191,500	184,300	183,200	4.5***	0.5***	-3.8***	-0.1
	(285)	(275)	(287)	(268)	(0.2)	(0.1)	(0.1)	(0.1)
W2 Earnings								
Average	63,550	67,310	63,590	63,380	5.9***	0.1	-5.5***	-0.3
	(338)	(229)	(118)	(106)	(0.5)	(0.5)	(0.3)	(0.5)
50th Percentile	30,720	35,840	30,320	30,640	16.7***	-1.3***	-15.4***	-0.2**
	(116)	(106)	(130)	(114)	(0.4)	(0.1)	(0.3)	(0.1)
75th Percentile	87,890	93,910	88,100	87,780	6.8***	0.2**	-6.2***	-0.1
	(150)	(161)	(156)	(141)	(0.2)	(0.1)	(0.2)	(0.1)
90th Percentile	156,600	162,900	157,300	156,400	4.0***	0.4***	-3.4***	-0.1***
	(246)	(244)	(252)	(234)	(0.2)	Z	(0.1)	Z
In Any Admin Data	86.2	88.3	86.0	86.2	2.5***	-0.2***	-2.7***	Z
	Z	Z	Z	Z	(0.1)	Z	Z	Z
Demographic Characteristics (Any Member Is)								
Asian	5.5	5.7	5.6	5.5	3.6***	0.6***	-2.8***	0.1
	Z	Z	Z	Z	(0.5)	(0.1)	(0.5)	(0.1)
Black	13.0	12.8	12.6	13.0	-1.5***	-3.0***	-1.5***	0.3***
	Z	Z	Z	Z	(0.3)	(0.1)	(0.3)	(0.1)
Other Race	7.5	7.2	7.5	7.6	-3.9***	-1.1***	3.0***	0.4***
	Z	Z	Z	Z	(0.4)	(0.1)	(0.4)	(0.1)
Native American or Alaskan Native	1.6	1.5	1.5	1.6	-4.1***	-1.2***	3.0***	0.3*
	Z	Z	Z	Z	(0.8)	(0.2)	(0.9)	(0.2)
White	66.0	68.6	66.1	65.9	4.0***	0.2***	-3.7***	-0.1***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	Z	(0.1)	Z
Hispanic	13.0	13.1	12.9	13.1	0.6*	-1.3***	-1.9***	0.5***
	Z	Z	Z	Z	(0.3)	(0.1)	(0.3)	(0.1)
Non-Citizen	11.4	11.5	11.4	11.4	0.9***	-0.5***	-1.4***	0.1
	Z	Z	Z	Z	(0.3)	(0.1)	(0.3)	(0.1)
Foreign Born	18.0	18.4	17.9	18.0	2.3***	-0.3*	-2.5***	0.3*
	Z	Z	Z	Z	(0.2)	(0.2)	(0.3)	(0.2)
Female	71.1	73.8	71.0	71.2	3.9***	-0.1**	-3.8***	0.2***
	(0.1)	(0.1)	(0.1)	Z	(0.1)	Z	(0.1)	Z
Male	67.5	70.1	67.5	67.5	3.8***	-0.1***	-3.7***	Z
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	Z	(0.1)	Z

Source: U.S. Census Bureau, 2020 American Community Survey 1-year data linked to decennial census, administrative, and third-party data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)].

Notes: This table provides information on how well the experimental entropy balance weights and survey weights match estimates of the distribution of income and demographic characteristics in the linked data. Columns (1)-(3) respectively show address-level estimates from linked data using the survey base weights (based on probability of selection into the sample and CAPI subsampling for all occupied units), final survey weights, and entropy balance weights. The estimates in Column (1) are the targets for the entropy balancing procedure. Column (4) shows estimates at the household level using the average weights of the individual members (as shown in Equation (7)), which is the target of the entropy balancing person-level weights in 2.A (refer to Table 1). Columns (5)-(8) show the percent difference between the various estimates in (1)-(4). Percentile estimates are interpolated across bins of $2,500 and include addresses with 0 income. ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates an estimate or standard error rounds to zero (is less than < 0.05) for any percent or percent difference.

Appendix Table 7: 10th Percentile of Real Household Income by State

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	15,330	16,280	15,300	15,330	-0.18	-5.83***	6.20***	0.20	-6.00***
State									
Alabama	11,630	13,300	11,550	12,050	-0.70	-9.40***	14.36***	4.33***	-10.03***
Alaska	19,220	20,390	19,120	20,220	-0.47	-0.83	6.09	5.75	-0.33
Arizona	15,850	17,170	15,600	16,010	-1.57	-6.77***	8.33***	2.63**	-5.70**
Arkansas	12,290	13,670	12,050	12,440	-1.96	-8.95***	11.23***	3.24**	-7.99*
California	17,800	18,990	17,720	17,930	-0.46	-5.58***	6.69***	1.19*	-5.50***
Colorado	19,840	20,600	19,460	19,620	-1.92	-4.78***	3.83	0.82	-3.01
Connecticut	16,700	17,840	16,770	16,620	0.40	-6.84**	6.83*	-0.89	-7.72*
Delaware	16,380	19,810	16,850	17,950	2.86	-9.36*	20.94***	6.53	-14.41
District of Columbia	12,760	12,950	12,210	12,240	-4.26	-5.50	1.49	0.25	-1.24
Florida	15,060	15,630	15,180	14,800	0.78	-5.29***	3.78**	-2.50***	-6.29***
Georgia	14,630	15,600	14,340	14,040	-1.95	-10.04***	6.63**	-2.09*	-8.72***
Hawaii	19,610	22,000	19,250	21,150	-1.83	-3.86	12.19**	9.87***	-2.32
Idaho	17,140	18,840	17,050	17,700	-0.50	-6.05*	9.92**	3.81*	-6.11
Illinois	15,640	16,160	15,660	15,340	0.09	-5.02***	3.32	-2.04**	-5.37**
Indiana	15,200	16,350	15,230	15,520	0.18	-5.06***	7.57***	1.90	-5.66**
Iowa	15,970	17,050	15,840	16,560	-0.78	-2.88	6.76**	4.55***	-2.22
Kansas	15,790	16,170	15,610	16,290	-1.11	0.71	2.41	4.36***	1.95
Kentucky	11,840	12,790	11,940	12,350	0.84	-3.48	8.02**	3.43**	-4.59
Louisiana	9,999	11,270	10,210	10,620	2.08	-5.77**	12.71***	4.02***	-8.70**
Maine	15,430	15,360	15,300	14,640	-0.81	-4.65	-0.45	-4.31*	-3.86
Maryland	20,140	21,980	19,810	19,880	-1.65	-9.57***	9.14***	0.35	-8.78**
Massachusetts	16,610	16,860	16,300	16,180	-1.85	-4.06**	1.51	-0.74	-2.24
Michigan	14,820	15,470	14,730	14,450	-0.60	-6.61***	4.39**	-1.90*	-6.29***
Minnesota	18,980	20,730	19,270	19,740	1.53	-4.76***	9.22***	2.44	-6.78**
Mississippi	10,570	11,000	10,280	10,550	-2.75	-4.09*	4.07	2.63**	-1.44
Missouri	14,100	15,350	14,010	14,350	-0.61	-6.51***	8.87***	2.43*	-6.44**
Montana	14,890	14,180	15,070	14,440	1.15	1.88	-4.77	-4.18	0.59
Nebraska	16,810	17,220	16,540	17,390	-1.64	0.99	2.44	5.14***	2.70
Nevada	15,200	16,600	15,250	16,080	0.34	-3.13	9.21**	5.44***	-3.77
New Hampshire	20,280	22,130	21,030	21,080	3.68	-4.74	9.12	0.24	-8.88
New Jersey	19,420	19,800	19,100	18,930	-1.64	-4.43**	1.96	-0.89	-2.85
New Mexico	11,730	11,480	11,480	10,750	-2.09	-6.39***	-2.13	-6.36***	-4.23
New York	13,620	15,010	14,110	14,030	3.58***	-6.54***	10.21***	-0.57	-10.77***
North Carolina	14,120	14,380	14,010	13,690	-0.74	-4.79***	1.84	-2.28***	-4.13*
North Dakota	15,370	16,120	15,480	15,800	0.73	-2.02	4.88	2.07	-2.81
Ohio	14,380	15,400	14,070	14,250	-2.15*	-7.44***	7.09***	1.28	-5.81***
Oklahoma	13,100	14,170	13,150	13,090	0.38	-7.63***	8.17***	-0.46	-8.62***
Oregon	16,400	18,110	16,250	16,270	-0.94	-10.14***	10.43***	0.12	-10.30***
Pennsylvania	15,020	16,440	15,190	15,480	1.13	-5.81***	9.45***	1.91***	-7.54***
Rhode Island	14,890	16,600	16,240	15,990	9.08	-3.67	11.48	-1.54	-13.02
South Carolina	12,980	13,720	12,810	12,770	-1.31	-6.90***	5.70	-0.31	-6.01
South Dakota	16,360	16,610	15,840	15,870	-3.14	-4.45	1.53	0.19	-1.34
Tennessee	13,780	14,710	13,740	13,520	-0.24	-8.09***	6.75**	-1.60	-8.35***
Texas	15,510	16,600	15,550	15,280	0.28	-7.96***	7.03***	-1.74***	-8.76***
Utah	21,410	23,540	21,650	23,610	1.11	0.29	9.95***	9.05***	-0.90
Vermont	15,650	17,840	16,770	16,520	7.21	-7.42**	13.99*	-1.49	-15.48*
Virginia	18,090	20,010	17,820	18,800	-1.45	-6.02***	10.61***	5.50***	-5.11*
Washington	19,840	20,850	19,420	19,440	-2.12	-6.79***	5.09**	0.10	-4.99*
West Virginia	11,300	11,580	11,150	11,290	-1.26	-2.56	2.48	1.26	-1.22
Wisconsin	16,980	17,110	17,050	16,050	0.47	-6.24***	0.77	-5.87***	-6.63***
Wyoming	16,920	17,230	16,690	16,370	-1.38	-5.00	1.83	-1.92	-3.75

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](https://www.census.gov).
Notes: This table shows real household income at the 10th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Columns (1) and (2) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the percent difference each year between the production and experimental weights. Columns (7) and (8) show the year-to-year estimates for the production and experimental weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons.

Appendix Table 8: 25th Percentile of Real Household Income by State

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	33,410	35,540	33,870	33,840	1.37***	-4.81***	6.38***	-0.09	-6.46***
State									
Alabama	25,680	28,030	25,860	26,510	0.71	-5.43***	9.15***	2.51**	-6.64***
Alaska	41,210	45,560	41,640	45,000	1.05	-1.23	10.56**	8.07***	-2.49
Arizona	33,830	36,190	33,800	34,300	-0.09	-5.23***	6.98***	1.48*	-5.50***
Arkansas	25,080	27,030	25,080	25,080	-0.01	-7.21***	7.78***	Z	-7.78***
California	40,200	42,380	40,950	41,000	1.86***	-3.27***	5.42***	0.12	-5.30***
Colorado	41,540	42,960	41,530	41,970	-0.04	-2.32*	3.42*	1.06	-2.36
Connecticut	38,570	41,740	39,890	40,180	3.44**	-3.73***	8.22***	0.73	-7.49***
Delaware	37,220	36,720	38,990	35,650	4.76*	-2.89	-1.34	-8.57***	-7.22
District of Columbia	41,570	42,770	41,790	44,830	0.55	4.80	2.89	7.27	4.39
Florida	31,370	32,470	32,170	31,640	2.55***	-2.56***	3.51***	-1.65***	-5.15***
Georgia	31,570	33,670	31,740	31,240	0.52	-7.21***	6.65***	-1.58**	-8.23***
Hawaii	44,350	46,730	45,440	46,320	2.47	-0.88	5.37	1.94	-3.43
Idaho	33,660	36,410	33,460	35,020	-0.61	-3.81**	8.17***	4.66***	-3.51
Illinois	34,490	36,600	35,150	35,520	1.91***	-2.95***	6.12***	1.05*	-5.07***
Indiana	31,140	33,190	31,640	31,760	1.61*	-4.31***	6.58***	0.38	-6.20***
Iowa	33,550	35,310	33,660	33,580	0.34	-4.89***	5.25***	-0.24	-5.48**
Kansas	33,320	33,950	33,180	33,870	-0.43	-0.23	1.89	2.08	0.19
Kentucky	26,060	28,450	26,710	27,400	2.49*	-3.68***	9.17***	2.58**	-6.59***
Louisiana	23,210	26,030	23,880	24,510	2.88*	-5.82***	12.15***	2.64*	-9.51***
Maine	31,000	31,800	30,560	30,230	-1.41	-4.92***	2.58	-1.08	-3.66
Maryland	44,920	47,940	44,370	45,520	-1.21	-5.06***	6.72***	2.59***	-4.13*
Massachusetts	41,020	42,260	40,810	40,910	-0.51	-3.20**	3.02*	0.25	-2.78
Michigan	31,190	32,210	31,520	31,270	1.08*	-2.93***	3.27***	-0.79	-4.06***
Minnesota	40,540	42,000	40,680	40,530	0.33	-3.51***	3.60***	-0.37	-3.97***
Mississippi	22,180	23,410	22,360	21,940	0.81	-6.30***	5.55*	-1.88	-7.42**
Missouri	30,110	31,570	30,390	30,810	0.92	-2.41***	4.85***	1.38*	-3.47**
Montana	30,510	30,300	30,650	30,200	0.46	-0.32	-0.69	-1.47	-0.78
Nebraska	34,820	35,820	34,210	34,060	-1.73	-4.91***	2.87	-0.44	-3.31
Nevada	33,700	34,230	33,820	33,540	0.37	-2.01	1.57	-0.83	-2.40
New Hampshire	42,350	44,840	42,870	43,980	1.23	-1.93	5.88**	2.59	-3.29
New Jersey	42,910	44,580	43,330	42,150	0.96	-5.45***	3.89**	-2.72***	-6.62***
New Mexico	25,180	26,800	25,380	24,960	0.81	-6.87***	6.43*	-1.65	-8.09**
New York	33,740	35,500	34,860	34,390	3.33***	-3.14***	5.22***	-1.35**	-6.56***
North Carolina	29,940	31,170	30,140	30,120	0.68	-3.38***	4.11***	-0.07	-4.17***
North Dakota	33,550	35,210	33,520	33,690	-0.10	-4.32	4.95	0.51	-4.44
Ohio	30,480	32,080	30,710	30,890	0.75	-3.71***	5.25***	0.59	-4.66***
Oklahoma	28,370	30,130	28,740	27,890	1.32	-7.45***	6.20***	-2.96***	-9.16***
Oregon	35,330	38,470	35,290	35,520	-0.13	-7.66***	8.89***	0.65	-8.24***
Pennsylvania	32,380	34,890	32,590	32,650	0.67	-6.42***	7.75***	0.18	-7.57***
Rhode Island	34,760	38,150	36,430	37,250	4.80*	-2.36	9.75**	2.25	-7.50
South Carolina	29,400	30,230	29,510	28,400	0.38	-6.04***	2.82	-3.76***	-6.58***
South Dakota	32,190	34,460	32,780	32,480	1.82	-5.76	7.05	-0.92	-7.97
Tennessee	29,350	31,040	29,480	29,510	0.45	-4.92***	5.76***	0.10	-5.66***
Texas	33,100	36,000	33,850	33,850	2.28***	-6.00***	8.76***	Z	-8.76***
Utah	43,350	44,830	43,690	44,330	0.80	-1.12	3.41	1.46	-1.95
Vermont	33,330	37,170	35,350	35,170	6.07**	-5.36**	11.52***	-0.51	-12.03**
Virginia	39,340	42,210	39,750	40,540	1.03	-3.96***	7.30***	1.99**	-5.31***
Washington	41,880	43,880	41,790	42,060	-0.21	-4.16***	4.78***	0.65	-4.13**
West Virginia	24,510	24,060	24,520	23,770	0.05	-1.22	-1.84	-3.06**	-1.22
Wisconsin	34,630	35,920	35,110	34,130	1.41*	-4.97***	3.73***	-2.79***	-6.52***
Wyoming	34,170	35,360	35,040	35,940	2.57	1.62	3.48	2.57	-0.91

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](https://www.census.gov).

Notes: This table shows real household income at the 25th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Columns (1) and (2) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the percent difference each year between the production and experimental weights. Columns (7) and (8) show the year-to-year estimates for the production and experimental weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates an estimate rounds to zero (< 0.005 for percent differences).

Appendix Table 9: 75th Percentile of Real Household Income by State

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	117,000	121,500	118,700	119,300	1.49***	-1.77***	3.85***	0.51***	-3.34***
State									
Alabama	95,020	100,800	96,200	97,470	1.25	-3.29***	6.08***	1.32	-4.76***
Alaska	131,900	133,600	132,500	131,000	0.39	-1.94	1.29	-1.13	-2.42
Arizona	107,800	113,300	110,100	110,600	2.13***	-2.38**	5.10***	0.45	-4.65***
Arkansas	87,090	94,320	88,130	91,180	1.20	-3.33***	8.30***	3.46***	-4.84**
California	144,200	151,500	147,700	149,500	2.42***	-1.30***	5.06***	1.22***	-3.84***
Colorado	132,000	134,600	132,300	131,800	0.19	-2.09**	1.97*	-0.38	-2.35*
Connecticut	143,000	144,300	144,300	143,100	0.90	-0.83	0.91	-0.83	-1.74
Delaware	120,900	122,400	122,500	120,700	1.33	-1.38	1.24	-1.47	-2.71
District of Columbia	178,200	184,400	179,700	189,400	0.83	2.73	3.48	5.40*	1.92
Florida	103,700	108,700	107,900	109,000	4.08***	0.24	4.82***	1.02**	-3.80***
Georgia	109,200	117,400	110,600	113,000	1.33**	-3.75***	7.51***	2.17***	-5.34***
Hawaii	139,100	146,700	143,000	145,800	2.80**	-0.63	5.46***	1.96*	-3.51
Idaho	101,200	106,900	99,750	103,500	-1.46	-3.12*	5.63***	3.76***	-1.87
Illinois	122,900	126,200	123,500	123,200	0.48	-2.35***	2.69***	-0.24	-2.93***
Indiana	100,500	103,800	101,200	102,700	0.70*	-1.10	3.28***	1.48***	-1.80
Iowa	103,000	106,500	102,600	104,200	-0.42	-2.14***	3.40***	1.56**	-1.84
Kansas	105,400	108,000	105,100	105,800	-0.30	-2.03*	2.47*	0.67	-1.80
Kentucky	92,540	97,360	93,810	95,150	1.37*	-2.27***	5.21***	1.43*	-3.78***
Louisiana	96,390	101,200	99,150	98,680	2.87***	-2.50**	4.99***	-0.47	-5.46***
Maine	101,600	106,400	101,800	101,800	0.19	-4.34***	4.72**	Z	-4.72**
Maryland	148,300	155,300	148,900	151,100	0.39	-2.67***	4.72***	1.48***	-3.24***
Massachusetts	153,300	156,600	154,000	155,100	0.50	-0.94	2.15**	0.71	-1.44
Michigan	103,100	108,100	104,100	106,000	0.98***	-2.01***	4.85***	1.83***	-3.02***
Minnesota	124,300	128,900	124,300	125,300	0.01	-2.83***	3.70***	0.80*	-2.90***
Mississippi	83,430	90,600	85,380	86,820	2.33**	-4.17***	8.59***	1.69	-6.91***
Missouri	100,500	103,200	101,200	102,100	0.75	-1.03	2.69***	0.89*	-1.80
Montana	98,960	101,700	98,050	100,000	-0.91	-1.65	2.77	1.99	-0.78
Nebraska	106,000	108,500	105,900	106,600	-0.10	-1.78*	2.36	0.66	-1.70
Nevada	108,400	112,100	108,900	110,500	0.49	-1.36	3.41***	1.47**	-1.94
New Hampshire	130,700	132,400	132,300	133,700	1.24	0.97	1.30	1.06	-0.24
New Jersey	153,300	155,200	154,600	152,400	0.86**	-1.82***	1.24	-1.42***	-2.66***
New Mexico	93,380	99,580	94,940	95,160	1.67	-4.44**	6.64***	0.23	-6.41**
New York	133,800	135,300	136,800	134,000	2.28***	-0.98**	1.12**	-2.05***	-3.17***
North Carolina	101,500	106,000	102,400	104,300	0.89**	-1.62***	4.43***	1.86***	-2.58***
North Dakota	110,200	111,400	110,300	106,500	0.11	-4.39**	1.09	-3.45*	-4.53
Ohio	101,900	105,300	102,400	102,400	0.48	-2.77***	3.34***	Z	-3.34***
Oklahoma	95,990	100,300	97,000	95,870	1.06	-4.40***	4.49***	-1.16**	-5.65***
Oregon	115,600	122,200	116,900	117,000	1.15	-4.22***	5.71***	0.09	-5.62***
Pennsylvania	111,600	115,700	112,400	112,300	0.79*	-2.97***	3.67***	-0.09	-3.76***
Rhode Island	120,200	126,100	124,000	124,800	3.13**	-1.03	4.91**	0.65	-4.26
South Carolina	100,100	103,200	100,600	100,600	0.50	-2.52**	3.10**	Z	-3.10**
South Dakota	101,100	101,300	101,200	99,310	0.05	-1.93	0.20	-1.87	-2.07
Tennessee	98,430	101,100	99,710	99,350	1.30*	-1.76***	2.71***	-0.36	-3.07***
Texas	114,400	120,500	117,100	116,900	2.34***	-3.00***	5.33***	-0.17	-5.50***
Utah	121,300	126,300	121,600	125,400	0.19	-0.75	4.12***	3.13***	-1.00
Vermont	107,800	115,100	107,700	112,900	-0.16	-1.92	6.77***	4.83***	-1.94
Virginia	135,500	141,900	137,500	140,100	1.48**	-1.25***	4.72***	1.89***	-2.83**
Washington	135,000	140,200	135,800	138,600	0.55	-1.18*	3.85***	2.06***	-1.79
West Virginia	87,510	90,930	87,370	86,940	-0.16	-4.39***	3.91	-0.49	-4.40
Wisconsin	107,000	109,900	107,300	107,400	0.31	-2.26***	2.71***	0.09	-2.62**
Wyoming	107,000	112,700	110,900	108,200	3.62*	-3.96**	5.33*	-2.43	-7.76**

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year dataestimates. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Notes: This table shows real household income at the 75th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Columns (1) and (2) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the percent difference each year between the production and experimental weights. Columns (7) and (8) show the year-to-year estimates for the production and experimental weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates an estimate rounds to zero (< 0.005 for percent differences).

Appendix Table 10: 90th Percentile of Real Household Income by State

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	187,400	193,100	190,900	191,200	1.85***	-0.94***	3.04***	0.16	-2.88***
State									
Alabama	146,500	155,400	150,200	152,100	2.52**	-2.08*	6.08***	1.26*	-4.81***
Alaska	197,800	193,100	197,000	193,100	-0.39	-0.03	-2.38	-1.98	0.40
Arizona	169,000	176,200	174,400	175,700	3.16***	-0.28	4.26***	0.75	-3.51***
Arkansas	137,300	145,000	140,100	142,000	2.08*	-2.07*	5.61***	1.36	-4.25**
California	232,900	243,100	239,900	240,600	3.00***	-1.02*	4.38***	0.29	-4.09***
Colorado	203,900	209,500	205,100	207,000	0.56	-1.16	2.75**	0.93	-1.82
Connecticut	231,400	232,800	233,400	230,200	0.87	-1.11	0.61	-1.37	-1.98
Delaware	180,700	188,400	187,900	180,200	3.96**	-4.31	4.26	-4.10**	-8.36
District of Columbia	250,000+	250,000+	250,000+	250,000+	N	N	N	N	N
Florida	167,000	173,300	174,900	175,200	4.75***	1.12	3.77***	0.17	-3.60***
Georgia	175,900	186,500	178,500	179,400	1.47*	-3.80***	6.03***	0.50	-5.52***
Hawaii	207,700	223,900	217,000	215,700	4.45***	-3.68	7.80**	-0.60	-8.40**
Idaho	152,500	157,100	152,300	158,300	-0.15	0.78	3.02	3.94***	0.92
Illinois	192,800	198,600	196,200	195,400	1.80***	-1.64*	3.01***	-0.41	-3.42***
Indiana	152,100	153,800	152,700	152,800	0.36	-0.67	1.12	0.07	-1.05
Iowa	154,400	156,900	153,800	157,100	-0.38	0.17	1.62	2.15**	0.53
Kansas	160,500	168,500	160,900	162,300	0.24	-3.65***	4.98***	0.87	-4.11**
Kentucky	142,700	147,400	144,800	145,200	1.48*	-1.45	3.29**	0.28	-3.02*
Louisiana	152,900	158,400	156,500	155,300	2.34**	-1.97	3.60**	-0.77	-4.36**
Maine	155,200	159,500	154,500	156,700	-0.41	-1.75	2.77	1.42	-1.35
Maryland	231,100	231,500	233,300	231,200	0.94	-0.11	0.17	-0.90	-1.07
Massachusetts	241,600	249,500	243,100	249,300	0.62	-0.09	3.27**	2.55***	-0.72
Michigan	161,100	167,300	163,000	164,300	1.22*	-1.76**	3.85***	0.80	-3.05**
Minnesota	188,600	194,300	187,500	191,200	-0.60	-1.63*	3.02***	1.97***	-1.05
Mississippi	133,700	141,100	136,600	137,100	2.20**	-2.85*	5.53***	0.37	-5.17**
Missouri	154,000	157,100	156,200	156,700	1.40**	-0.29	2.01*	0.32	-1.69
Montana	149,200	151,400	150,300	151,400	0.78	-0.06	1.47	0.73	-0.74
Nebraska	160,800	165,700	159,600	161,500	-0.79	-2.55**	3.05	1.19	-1.86
Nevada	165,000	169,800	168,400	172,900	2.06	1.82	2.91	2.67**	-0.24
New Hampshire	199,700	200,100	203,100	201,000	1.73	0.44	0.20	-1.03	-1.23
New Jersey	244,700	245,000	247,900	242,900	1.30**	-0.86	0.12	-2.02***	-2.14
New Mexico	148,600	151,100	152,400	148,500	2.54**	-1.72	1.68	-2.56*	-4.24*
New York	220,500	220,000	226,900	218,700	2.88***	-0.58	-0.23	-3.61***	-3.39***
North Carolina	161,100	168,000	163,100	166,800	1.27*	-0.70	4.28***	2.27***	-2.01
North Dakota	165,800	165,600	163,900	160,800	-1.17	-2.94	-0.12	-1.89	-1.77
Ohio	158,000	161,800	159,400	159,500	0.94	-1.44**	2.41***	0.06	-2.34**
Oklahoma	148,800	152,500	150,700	147,100	1.30*	-3.54***	2.49	-2.39***	-4.88***
Oregon	176,100	189,700	177,700	182,400	0.91	-3.86***	7.72***	2.64***	-5.08***
Pennsylvania	175,600	182,000	178,900	177,600	1.86***	-2.43***	3.64***	-0.73	-4.37***
Rhode Island	181,000	192,500	193,300	187,200	6.81***	-2.77	6.35	-3.16	-9.51**
South Carolina	158,500	160,300	159,200	159,100	0.45	-0.75	1.14	-0.06	-1.20
South Dakota	150,800	151,100	149,000	150,000	-1.20	-0.68	0.20	0.67	0.47
Tennessee	154,300	157,000	155,900	155,900	1.05	-0.75	1.75	Z	-1.75
Texas	182,700	190,300	187,200	186,800	2.44***	-1.83***	4.16***	-0.21	-4.37***
Utah	179,200	183,700	183,800	185,600	2.57**	1.07	2.51	0.98	-1.53
Vermont	164,300	165,700	164,200	168,200	-0.05	1.55	0.85	2.44	1.58
Virginia	218,400	222,000	221,500	223,400	1.46**	0.63	1.65	0.86	-0.79
Washington	211,600	217,400	212,200	218,100	0.33	0.36	2.74**	2.78***	0.04
West Virginia	133,500	138,200	135,200	134,800	1.23	-2.44	3.52	-0.30	-3.82
Wisconsin	158,800	163,100	159,900	159,600	0.72	-2.14**	2.71***	-0.19	-2.90**
Wyoming	157,400	161,400	158,900	161,800	1.01	0.28	2.54	1.83	-0.72

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Notes: This table shows real household income at the 90th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Columns (1) and (2) show the estimates in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the estimates in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the percent difference each year between the production and experimental weights. Columns (7) and (8) show the year-to-year estimates for the production and experimental weights. Column (9) shows the difference between the year-to-year estimates in (7) and (8). ***, **, and * indicate significance at the 1-, 5-, and 10-percent level for comparisons. Z indicates an estimate rounds to zero (< 0.005 for percent differences). Estimates for the District of Columbia exceed the usual ACS top code for percentile estimates of $250,000 and are top coded as a result, with estimates in Columns (5)-(8) replaced with N due to the top-coding.

Appendix Table 11: ACS Estimates and Margins of Error for Figures 10, 11, 12, 13, 15, and 16

Description	Estimate	Margin of Error (MOE)
Figure 10: Share of Single-Family (Attached or Detached) Units (2016-2020)		
2016 ACS Survey Weights	67.4	0.1
2017 ACS Survey Weights	67.5	0.1
2018 ACS Survey Weights	67.2	0.1
2019 ACS Survey Weights	67.1	0.1
2020 ACS Survey Weights	68.9	0.1
2019 ACS EBW	67.6	0.1
2020 ACS EBW	67.7	0.1
Figure 11: Number of Owner-Occupied Units (2016-2020)		
2016 ACS Survey Weights	75,022,569	227,992
2017 ACS Survey Weights	76,684,018	243,713
2018 ACS Survey Weights	77,708,394	235,977
2019 ACS Survey Weights	78,724,862	240,723
2020 ACS Survey Weights	83,210,000	121,700
2019 ACS EBW	80,180,000	98,770
2020 ACS EBW	81,400,000	83,870
Figure 12: Share of Owner-Occupied Units (2016-2020)		
2016 ACS Survey Weights	63.1	0.1
2017 ACS Survey Weights	63.9	0.1
2018 ACS Survey Weights	63.9	0.1
2019 ACS Survey Weights	64.1	0.1
2020 ACS Survey Weights	66.9	0.1
2019 ACS EBW	65.3	0.1
2020 ACS EBW	65.5	0.1
Figure 13: Number of Noncitizens (2012-2020)		
2012 ACS Survey Weights	22,138,421	109,661
2013 ACS Survey Weights	22,053,356	116,246
2014 ACS Survey Weights	22,407,056	130,473
2015 ACS Survey Weights	22,593,269	114,018
2016 ACS Survey Weights	22,500,973	129,193
2017 ACS Survey Weights	22,577,123	141,327
2018 ACS Survey Weights	22,098,984	146,776
2019 ACS Survey Weights	21,749,984	160,360
2020 ACS Survey Weights	20,130,000	125,800
2019 ACS EBW	20,310,000	40,900
2020 ACS EBW	20,210,000	57,670

Figure 15: Unemployment Rate from 2010 to 2020

2010 ACS Survey Weights	10.8	0.1
2011 ACS Survey Weights	10.3	0.1
2012 ACS Survey Weights	9.4	0.1
2013 ACS Survey Weights	8.4	0.1
2014 ACS Survey Weights	7.2	0.1
2015 ACS Survey Weights	6.3	0.1
2016 ACS Survey Weights	5.8	0.1
2017 ACS Survey Weights	5.3	0.1
2018 ACS Survey Weights	4.9	0.1
2019 ACS Survey Weights	4.5	0.1
2020 ACS Survey Weights	6.5	0.1
2019 ACS EBW	4.6	0.1
2020 ACS EBW	6.8	0.1

Figure 16: Civilian Labor Force Participation in 2019 and 2020

2019 ACS Survey Weights	63.4	0.1
2020 ACS Survey Weights	62.6	0.1
2019 ACS EBW	63.5	0.1
2020 ACS EBW	62.3	0.1

Appendix Table 12: Year-to-Year Change in Real Household Income Across the Distribution, Survey vs. EBW

	Survey		EBW	
	Percent Difference	Standard Error	Percent Difference	Standard Error
5th Percentile	5.9	0.6	-0.1	0.2
10th Percentile	6.2	0.4	0.2	0.2
15th Percentile	5.5	0.3	-0.2	0.1
20th Percentile	6.9	0.3	-0.5	0.2
25th Percentile	6.4	0.3	-0.1	0.2
30th Percentile	4.9	0.2	0.0	0.1
35th Percentile	5.8	0.2	0.0	0.1
40th Percentile	5.8	0.2	-0.1	0.1
45th Percentile	4.5	0.2	0.3	0.1
50th Percentile	5.5	0.2	0.2	0.1
55th Percentile	4.7	0.2	0.2	0.1
60th Percentile	5.0	0.2	0.4	0.1
65th Percentile	4.8	0.2	0.5	0.1
70th Percentile	4.3	0.2	0.6	0.1
75th Percentile	3.9	0.2	0.5	0.1
80th Percentile	3.7	0.2	0.6	0.1
85th Percentile	3.6	0.2	0.3	0.1
90th Percentile	3.0	0.2	0.2	0.1
95th Percentile	2.1	0.3	-0.7	0.1

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Notes: This table shows percentage difference estimates and standard errors of the change in real household income (adjusted by the CPI-U-RS) between 2019 and 2020 using the survey and experimental entropy balance weights at each 5th percentile from the 5th to 95th. These percentage difference estimates are illustrated in Figure 14. All estimates are linear interpolations across bins of $2,500.

Appendix Table 13: Poverty Rate by Age, Standard Errors

	2019		2020		Difference (EBW-Survey)		Year-to-Year Change		Diff-in-Diff
	Survey	EBW	Survey	EBW	2019	2020	Survey	EBW	
Poverty	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overall	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.04)	(0.06)	(0.01)	(0.05)
Under 18 years	(0.11)	(0.01)	(0.10)	(0.02)	(0.11)	(0.10)	(0.13)	(0.03)	(0.12)
18 to 64 years	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.04)	(0.05)	(0.01)	(0.05)
65 years and over	(0.04)	(0.01)	(0.06)	(0.02)	(0.04)	(0.06)	(0.08)	(0.02)	(0.08)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Notes: This table shows standard errors of poverty rates by age using the survey and entropy balance weights. Point estimates associated with this table were shown in Table 4. Columns (1) and (3) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (2) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy balance weights. Columns (5) and (6) show the standard errors of the percentage-point difference each year between the production and entropy balance weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and entropy balance weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).

Appendix Table 14: Poverty Rate by State, Standard Errors

	2019		2020		Difference (EBW-Survey)		Year-to-Year Change		Diff-in-Diff
	Survey	EBW	Survey	EBW	2019	2020	Survey	EBW	
Poverty	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.04)	(0.06)	(0.01)	(0.05)
State									
Alabama	(0.32)	(0.09)	(0.32)	(0.11)	(0.32)	(0.32)	(0.46)	(0.14)	(0.47)
Alaska	(0.67)	(0.20)	(0.49)	(0.23)	(0.63)	(0.50)	(0.92)	(0.29)	(0.88)
Arizona	(0.29)	(0.06)	(0.35)	(0.08)	(0.28)	(0.34)	(0.43)	(0.10)	(0.43)
Arkansas	(0.35)	(0.12)	(0.42)	(0.15)	(0.32)	(0.44)	(0.57)	(0.18)	(0.57)
California	(0.11)	(0.02)	(0.13)	(0.03)	(0.11)	(0.12)	(0.19)	(0.04)	(0.18)
Colorado	(0.22)	(0.06)	(0.25)	(0.07)	(0.22)	(0.24)	(0.33)	(0.10)	(0.32)
Connecticut	(0.24)	(0.08)	(0.34)	(0.12)	(0.24)	(0.33)	(0.42)	(0.14)	(0.41)
Delaware	(0.71)	(0.20)	(0.81)	(0.24)	(0.67)	(0.75)	(1.10)	(0.31)	(1.02)
District of Columbia	(0.77)	(0.24)	(0.84)	(0.30)	(0.73)	(0.82)	(1.22)	(0.42)	(1.14)
Florida	(0.16)	(0.04)	(0.20)	(0.05)	(0.15)	(0.19)	(0.25)	(0.07)	(0.24)
Georgia	(0.21)	(0.06)	(0.28)	(0.07)	(0.21)	(0.28)	(0.35)	(0.10)	(0.35)
Hawaii	(0.51)	(0.11)	(0.51)	(0.11)	(0.49)	(0.50)	(0.71)	(0.15)	(0.71)
Idaho	(0.48)	(0.15)	(0.46)	(0.18)	(0.47)	(0.42)	(0.69)	(0.21)	(0.65)
Illinois	(0.19)	(0.03)	(0.16)	(0.06)	(0.18)	(0.15)	(0.23)	(0.07)	(0.21)
Indiana	(0.23)	(0.07)	(0.26)	(0.09)	(0.22)	(0.23)	(0.34)	(0.11)	(0.33)
Iowa	(0.32)	(0.10)	(0.29)	(0.11)	(0.30)	(0.29)	(0.41)	(0.15)	(0.38)
Kansas	(0.30)	(0.09)	(0.36)	(0.11)	(0.28)	(0.35)	(0.50)	(0.15)	(0.48)
Kentucky	(0.32)	(0.10)	(0.28)	(0.13)	(0.31)	(0.30)	(0.41)	(0.15)	(0.44)
Louisiana	(0.39)	(0.10)	(0.42)	(0.14)	(0.39)	(0.40)	(0.54)	(0.18)	(0.52)
Maine	(0.44)	(0.16)	(0.51)	(0.17)	(0.40)	(0.48)	(0.64)	(0.23)	(0.61)
Maryland	(0.21)	(0.06)	(0.27)	(0.07)	(0.21)	(0.27)	(0.36)	(0.10)	(0.38)
Massachusetts	(0.18)	(0.05)	(0.22)	(0.07)	(0.17)	(0.23)	(0.30)	(0.09)	(0.30)
Michigan	(0.19)	(0.05)	(0.20)	(0.07)	(0.18)	(0.20)	(0.28)	(0.08)	(0.27)
Minnesota	(0.20)	(0.05)	(0.24)	(0.08)	(0.20)	(0.22)	(0.29)	(0.09)	(0.27)
Mississippi	(0.50)	(0.13)	(0.52)	(0.17)	(0.48)	(0.47)	(0.78)	(0.19)	(0.73)
Missouri	(0.24)	(0.08)	(0.27)	(0.09)	(0.24)	(0.26)	(0.36)	(0.11)	(0.37)
Montana	(0.46)	(0.17)	(0.49)	(0.20)	(0.45)	(0.52)	(0.67)	(0.28)	(0.69)
Nebraska	(0.31)	(0.10)	(0.35)	(0.12)	(0.28)	(0.35)	(0.44)	(0.17)	(0.41)
Nevada	(0.38)	(0.09)	(0.45)	(0.12)	(0.36)	(0.45)	(0.54)	(0.16)	(0.54)
New Hampshire	(0.34)	(0.11)	(0.43)	(0.19)	(0.32)	(0.43)	(0.52)	(0.22)	(0.51)
New Jersey	(0.18)	(0.05)	(0.24)	(0.06)	(0.19)	(0.25)	(0.32)	(0.08)	(0.33)
New Mexico	(0.45)	(0.17)	(0.58)	(0.20)	(0.42)	(0.54)	(0.63)	(0.26)	(0.60)
New York	(0.15)	(0.04)	(0.18)	(0.04)	(0.14)	(0.18)	(0.24)	(0.05)	(0.23)
North Carolina	(0.21)	(0.06)	(0.26)	(0.06)	(0.21)	(0.26)	(0.34)	(0.08)	(0.34)
North Dakota	(0.50)	(0.22)	(0.54)	(0.39)	(0.45)	(0.63)	(0.73)	(0.47)	(0.80)
Ohio	(0.17)	(0.05)	(0.22)	(0.07)	(0.18)	(0.21)	(0.28)	(0.08)	(0.28)
Oklahoma	(0.24)	(0.07)	(0.28)	(0.08)	(0.26)	(0.27)	(0.37)	(0.11)	(0.38)
Oregon	(0.25)	(0.07)	(0.32)	(0.10)	(0.24)	(0.32)	(0.41)	(0.12)	(0.40)
Pennsylvania	(0.19)	(0.04)	(0.17)	(0.05)	(0.19)	(0.17)	(0.27)	(0.07)	(0.26)
Rhode Island	(0.58)	(0.20)	(0.59)	(0.22)	(0.53)	(0.57)	(0.81)	(0.29)	(0.77)
South Carolina	(0.33)	(0.10)	(0.32)	(0.14)	(0.33)	(0.31)	(0.49)	(0.18)	(0.49)
South Dakota	(0.57)	(0.18)	(0.52)	(0.24)	(0.58)	(0.54)	(0.78)	(0.33)	(0.81)
Tennessee	(0.24)	(0.07)	(0.26)	(0.09)	(0.22)	(0.26)	(0.33)	(0.12)	(0.33)
Texas	(0.15)	(0.03)	(0.20)	(0.05)	(0.14)	(0.20)	(0.24)	(0.06)	(0.24)
Utah	(0.30)	(0.08)	(0.34)	(0.08)	(0.29)	(0.35)	(0.48)	(0.12)	(0.47)
Vermont	(0.46)	(0.20)	(0.51)	(0.20)	(0.49)	(0.49)	(0.60)	(0.29)	(0.61)
Virginia	(0.18)	(0.05)	(0.21)	(0.06)	(0.18)	(0.21)	(0.27)	(0.09)	(0.27)
Washington	(0.21)	(0.06)	(0.23)	(0.08)	(0.20)	(0.23)	(0.30)	(0.10)	(0.29)
West Virginia	(0.49)	(0.14)	(0.54)	(0.18)	(0.46)	(0.53)	(0.70)	(0.21)	(0.69)
Wisconsin	(0.20)	(0.06)	(0.22)	(0.05)	(0.19)	(0.21)	(0.31)	(0.08)	(0.30)
Wyoming	(0.61)	(0.25)	(0.59)	(0.35)	(0.54)	(0.67)	(0.90)	(0.41)	(0.86)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Notes: This table shows standard errors of poverty rates by state. Point estimates associated with this table were shown in Table 5. Columns (1) and (3) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (2) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy balance weights. Columns (5) and (6) show the standard error of the percent difference each year between the production and entropy balance weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and entropy balance weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).

Appendix Table 15: 10th Percentile of Real Household Income by State, Standard Errors

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	(34)	(46)	(15)	(21)	(0.38)	(0.17)	(0.23)	(0.25)	(0.41)
State									
Alabama	(175)	(262)	(86)	(107)	(2.84)	(1.21)	(1.53)	(1.84)	(3.08)
Alaska	(925)	(1,045)	(562)	(642)	(7.46)	(4.58)	(5.48)	(5.40)	(8.75)
Arizona	(253)	(325)	(97)	(129)	(2.68)	(1.05)	(1.70)	(1.78)	(2.88)
Arkansas	(218)	(430)	(110)	(153)	(4.01)	(1.58)	(1.77)	(2.88)	(4.31)
California	(138)	(225)	(68)	(94)	(1.51)	(0.66)	(0.83)	(1.17)	(1.65)
Colorado	(415)	(374)	(196)	(214)	(2.87)	(1.50)	(1.84)	(1.82)	(3.24)
Connecticut	(317)	(592)	(162)	(250)	(4.08)	(1.77)	(2.25)	(3.18)	(4.45)
Delaware	(716)	(992)	(400)	(564)	(8.04)	(4.19)	(4.38)	(4.83)	(9.07)
District of Columbia	(918)	(1,693)	(314)	(409)	(15.15)	(4.22)	(6.62)	(11.38)	(15.72)
Florida	(146)	(205)	(62)	(88)	(1.69)	(0.70)	(0.89)	(1.11)	(1.83)
Georgia	(197)	(316)	(107)	(125)	(2.59)	(1.13)	(1.40)	(1.89)	(2.83)
Hawaii	(868)	(722)	(502)	(337)	(6.18)	(3.36)	(4.79)	(3.13)	(7.03)
Idaho	(399)	(700)	(210)	(300)	(4.82)	(2.17)	(2.36)	(3.44)	(5.29)
Illinois	(195)	(256)	(71)	(112)	(2.08)	(0.84)	(1.23)	(1.49)	(2.25)
Indiana	(231)	(267)	(100)	(156)	(2.40)	(1.22)	(1.50)	(1.70)	(2.69)
Iowa	(275)	(384)	(133)	(176)	(3.03)	(1.42)	(1.63)	(2.05)	(3.34)
Kansas	(314)	(358)	(165)	(164)	(3.05)	(1.52)	(1.83)	(2.10)	(3.40)
Kentucky	(213)	(302)	(73)	(154)	(3.21)	(1.44)	(1.77)	(2.46)	(3.52)
Louisiana	(195)	(301)	(91)	(117)	(3.73)	(1.47)	(2.09)	(2.46)	(4.01)
Maine	(484)	(465)	(224)	(305)	(4.34)	(2.44)	(2.94)	(3.05)	(4.98)
Maryland	(398)	(420)	(205)	(295)	(3.00)	(1.82)	(1.83)	(2.09)	(3.51)
Massachusetts	(327)	(290)	(163)	(157)	(2.65)	(1.38)	(1.77)	(1.73)	(2.99)
Michigan	(208)	(230)	(97)	(118)	(2.13)	(1.03)	(1.39)	(1.50)	(2.37)
Minnesota	(262)	(329)	(134)	(257)	(2.30)	(1.51)	(1.44)	(1.57)	(2.75)
Mississippi	(233)	(249)	(80)	(107)	(3.28)	(1.31)	(2.02)	(2.12)	(3.53)
Missouri	(233)	(312)	(112)	(147)	(2.85)	(1.33)	(1.59)	(1.89)	(3.14)
Montana	(479)	(560)	(199)	(354)	(4.85)	(2.67)	(3.36)	(3.91)	(5.53)
Nebraska	(431)	(486)	(173)	(258)	(3.91)	(1.91)	(2.60)	(2.89)	(4.35)
Nevada	(395)	(507)	(169)	(192)	(4.38)	(1.72)	(2.83)	(2.99)	(4.70)
New Hampshire	(579)	(960)	(315)	(501)	(5.66)	(2.82)	(3.04)	(4.17)	(6.33)
New Jersey	(335)	(407)	(151)	(154)	(2.73)	(1.13)	(1.73)	(1.95)	(2.96)
New Mexico	(339)	(304)	(174)	(143)	(3.84)	(1.89)	(2.90)	(2.44)	(4.28)
New York	(135)	(203)	(77)	(96)	(1.85)	(0.87)	(0.97)	(1.35)	(2.04)
North Carolina	(197)	(226)	(80)	(94)	(2.14)	(0.87)	(1.41)	(1.47)	(2.31)
North Dakota	(708)	(614)	(375)	(439)	(6.27)	(3.76)	(4.61)	(4.39)	(7.31)
Ohio	(145)	(230)	(82)	(104)	(1.93)	(0.95)	(1.13)	(1.44)	(2.15)
Oklahoma	(235)	(286)	(99)	(109)	(2.92)	(1.12)	(1.85)	(1.93)	(3.13)
Oregon	(326)	(436)	(154)	(226)	(3.45)	(1.68)	(1.98)	(2.39)	(3.84)
Pennsylvania	(184)	(239)	(70)	(83)	(2.08)	(0.72)	(1.17)	(1.41)	(2.20)
Rhode Island	(696)	(707)	(516)	(324)	(7.05)	(3.71)	(5.65)	(3.97)	(7.97)
South Carolina	(358)	(294)	(142)	(155)	(3.69)	(1.64)	(2.74)	(2.23)	(4.04)
South Dakota	(628)	(686)	(261)	(404)	(5.73)	(3.03)	(3.68)	(4.05)	(6.48)
Tennessee	(211)	(292)	(114)	(123)	(2.68)	(1.21)	(1.54)	(1.93)	(2.94)
Texas	(148)	(194)	(62)	(64)	(1.61)	(0.57)	(0.86)	(1.09)	(1.71)
Utah	(479)	(533)	(256)	(295)	(3.50)	(1.88)	(2.11)	(2.23)	(3.97)
Vermont	(815)	(732)	(421)	(352)	(7.56)	(3.24)	(5.38)	(3.63)	(8.22)
Virginia	(278)	(375)	(132)	(154)	(2.68)	(1.17)	(1.49)	(1.69)	(2.92)
Washington	(310)	(374)	(174)	(246)	(2.50)	(1.55)	(1.41)	(1.86)	(2.94)
West Virginia	(338)	(433)	(110)	(172)	(4.91)	(1.84)	(2.73)	(3.80)	(5.24)
Wisconsin	(196)	(293)	(103)	(131)	(2.08)	(0.96)	(1.22)	(1.51)	(2.29)
Wyoming	(1,011)	(975)	(480)	(781)	(8.38)	(5.47)	(6.09)	(6.50)	(10.00)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](https://www.census.gov).
Notes: This table shows standard errors of real household income at the 10th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Point estimates associated with this table were shown in Appendix Table 7. Columns (1) and (2) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the standard errors of the percent difference each year between the production and experimental weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and experimental weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).

Appendix Table 16: 25th Percentile of Real Household Income by State, Standard Errors

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	(67)	(62)	(26)	(44)	(0.28)	(0.15)	(0.21)	(0.18)	(0.32)
State									
Alabama	(346)	(380)	(190)	(180)	(2.09)	(1.03)	(1.37)	(1.23)	(2.32)
Alaska	(947)	(1,423)	(653)	(1,095)	(4.29)	(3.13)	(2.62)	(3.63)	(5.31)
Arizona	(355)	(369)	(154)	(252)	(1.56)	(0.88)	(1.11)	(0.96)	(1.79)
Arkansas	(331)	(403)	(192)	(250)	(2.15)	(1.26)	(1.38)	(1.49)	(2.49)
California	(144)	(212)	(96)	(106)	(0.65)	(0.35)	(0.42)	(0.49)	(0.74)
Colorado	(439)	(603)	(197)	(272)	(1.82)	(0.81)	(0.96)	(1.37)	(1.99)
Connecticut	(473)	(478)	(310)	(327)	(1.82)	(1.13)	(1.39)	(1.05)	(2.14)
Delaware	(986)	(1,133)	(675)	(514)	(4.01)	(2.06)	(2.76)	(2.83)	(4.51)
District of Columbia	(1,457)	(1,880)	(695)	(1,754)	(5.78)	(4.56)	(3.53)	(4.68)	(7.37)
Florida	(158)	(261)	(97)	(104)	(0.98)	(0.44)	(0.52)	(0.68)	(1.07)
Georgia	(243)	(524)	(153)	(165)	(1.85)	(0.70)	(0.84)	(1.49)	(1.98)
Hawaii	(1,174)	(1,016)	(558)	(493)	(3.61)	(1.66)	(2.71)	(2.26)	(3.97)
Idaho	(515)	(716)	(348)	(463)	(2.70)	(1.76)	(1.64)	(1.88)	(3.22)
Illinois	(249)	(285)	(116)	(189)	(1.13)	(0.63)	(0.74)	(0.80)	(1.29)
Indiana	(263)	(431)	(151)	(165)	(1.65)	(0.71)	(0.87)	(1.16)	(1.80)
Iowa	(337)	(549)	(246)	(334)	(1.95)	(1.23)	(1.03)	(1.38)	(2.30)
Kansas	(449)	(602)	(270)	(405)	(2.27)	(1.48)	(1.37)	(1.73)	(2.71)
Kentucky	(368)	(419)	(174)	(203)	(2.23)	(1.01)	(1.37)	(1.29)	(2.45)
Louisiana	(372)	(516)	(183)	(275)	(2.86)	(1.39)	(1.70)	(1.78)	(3.18)
Maine	(571)	(616)	(339)	(350)	(2.74)	(1.59)	(1.75)	(1.88)	(3.17)
Maryland	(563)	(698)	(333)	(286)	(2.05)	(1.00)	(1.22)	(1.42)	(2.28)
Massachusetts	(425)	(580)	(243)	(276)	(1.77)	(0.90)	(0.92)	(1.26)	(1.99)
Michigan	(196)	(222)	(107)	(144)	(0.96)	(0.57)	(0.61)	(0.71)	(1.12)
Minnesota	(256)	(368)	(164)	(226)	(1.12)	(0.68)	(0.66)	(0.81)	(1.31)
Mississippi	(395)	(512)	(208)	(202)	(2.98)	(1.28)	(1.65)	(1.88)	(3.24)
Missouri	(281)	(263)	(166)	(173)	(1.31)	(0.80)	(0.89)	(0.89)	(1.53)
Montana	(611)	(629)	(308)	(393)	(2.86)	(1.62)	(2.14)	(1.98)	(3.29)
Nebraska	(473)	(581)	(292)	(406)	(2.18)	(1.46)	(1.50)	(1.55)	(2.62)
Nevada	(682)	(806)	(319)	(443)	(3.15)	(1.61)	(2.01)	(2.27)	(3.54)
New Hampshire	(678)	(1,042)	(579)	(726)	(2.99)	(2.19)	(1.85)	(2.57)	(3.70)
New Jersey	(468)	(673)	(228)	(193)	(1.94)	(0.68)	(1.10)	(1.43)	(2.05)
New Mexico	(485)	(674)	(329)	(303)	(3.37)	(1.75)	(1.87)	(2.35)	(3.80)
New York	(234)	(261)	(129)	(172)	(1.06)	(0.61)	(0.66)	(0.72)	(1.23)
North Carolina	(235)	(238)	(127)	(134)	(1.14)	(0.61)	(0.75)	(0.73)	(1.29)
North Dakota	(958)	(1,061)	(497)	(1,003)	(4.36)	(3.34)	(2.53)	(3.57)	(5.49)
Ohio	(172)	(204)	(124)	(127)	(0.89)	(0.58)	(0.61)	(0.64)	(1.06)
Oklahoma	(281)	(372)	(159)	(216)	(1.68)	(0.92)	(0.99)	(1.21)	(1.92)
Oregon	(352)	(639)	(208)	(289)	(2.11)	(1.01)	(1.06)	(1.52)	(2.34)
Pennsylvania	(202)	(340)	(118)	(154)	(1.25)	(0.60)	(0.68)	(0.88)	(1.38)
Rhode Island	(886)	(1,295)	(496)	(662)	(4.66)	(2.29)	(2.79)	(3.15)	(5.19)
South Carolina	(347)	(375)	(228)	(311)	(1.76)	(1.29)	(1.27)	(1.34)	(2.18)
South Dakota	(625)	(1,253)	(416)	(702)	(4.41)	(2.48)	(1.82)	(3.64)	(5.06)
Tennessee	(281)	(301)	(214)	(231)	(1.44)	(1.07)	(1.02)	(1.14)	(1.79)
Texas	(220)	(228)	(106)	(143)	(1.00)	(0.53)	(0.59)	(0.67)	(1.13)
Utah	(634)	(718)	(385)	(452)	(2.24)	(1.37)	(1.42)	(1.37)	(2.63)
Vermont	(816)	(1,033)	(531)	(711)	(4.13)	(2.50)	(2.73)	(2.70)	(4.83)
Virginia	(378)	(358)	(266)	(218)	(1.37)	(0.87)	(1.06)	(0.84)	(1.63)
Washington	(329)	(532)	(211)	(251)	(1.51)	(0.79)	(0.79)	(1.14)	(1.71)
West Virginia	(481)	(507)	(263)	(247)	(2.82)	(1.45)	(1.83)	(2.14)	(3.17)
Wisconsin	(302)	(329)	(161)	(244)	(1.31)	(0.83)	(0.76)	(0.90)	(1.55)
Wyoming	(1,342)	(1,370)	(728)	(861)	(5.71)	(3.25)	(3.92)	(3.98)	(6.57)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).

Notes: This table shows standard errors of real household income at the 25th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Point estimates associated with this table were shown in Appendix Table 8. Columns (1) and (2) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the standard errors of the percent difference each year between the production and experimental weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and experimental weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).

Appendix Table 17: Real Median Household Income by State, Standard Errors

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	(71)	(87)	(37)	(54)	(0.17)	(0.10)	(0.12)	(0.11)	(0.20)
State									
Alabama	(414)	(614)	(320)	(437)	(1.45)	(1.03)	(0.75)	(1.12)	(1.78)
Alaska	(1,719)	(1,686)	(963)	(1,056)	(3.24)	(1.90)	(2.09)	(1.85)	(3.75)
Arizona	(380)	(589)	(274)	(379)	(1.15)	(0.74)	(0.65)	(0.83)	(1.36)
Arkansas	(553)	(927)	(291)	(319)	(2.23)	(0.87)	(1.16)	(1.48)	(2.39)
California	(201)	(365)	(183)	(253)	(0.52)	(0.38)	(0.31)	(0.43)	(0.64)
Colorado	(673)	(735)	(366)	(501)	(1.30)	(0.80)	(0.88)	(0.88)	(1.52)
Connecticut	(762)	(778)	(401)	(637)	(1.38)	(0.92)	(1.00)	(0.97)	(1.66)
Delaware	(1,022)	(1,836)	(621)	(1,128)	(2.98)	(1.77)	(1.64)	(2.47)	(3.47)
District of Columbia	(1,709)	(2,777)	(1,436)	(2,393)	(3.54)	(2.89)	(1.97)	(2.67)	(4.57)
Florida	(235)	(409)	(134)	(172)	(0.79)	(0.35)	(0.40)	(0.58)	(0.87)
Georgia	(394)	(501)	(314)	(433)	(1.05)	(0.85)	(0.71)	(0.80)	(1.35)
Hawaii	(1,269)	(1,388)	(678)	(730)	(2.28)	(1.15)	(1.50)	(1.55)	(2.55)
Idaho	(679)	(1,270)	(461)	(708)	(2.37)	(1.42)	(1.21)	(1.92)	(2.77)
Illinois	(311)	(383)	(170)	(230)	(0.72)	(0.41)	(0.42)	(0.51)	(0.82)
Indiana	(438)	(439)	(289)	(249)	(1.10)	(0.65)	(0.72)	(0.67)	(1.28)
Iowa	(516)	(691)	(293)	(320)	(1.40)	(0.70)	(0.78)	(0.96)	(1.57)
Kansas	(570)	(902)	(347)	(630)	(1.71)	(1.15)	(0.97)	(1.49)	(2.06)
Kentucky	(503)	(532)	(310)	(433)	(1.42)	(0.99)	(0.93)	(0.89)	(1.73)
Louisiana	(390)	(806)	(374)	(401)	(1.76)	(1.02)	(0.91)	(1.41)	(2.04)
Maine	(927)	(1,085)	(639)	(646)	(2.41)	(1.51)	(1.38)	(1.68)	(2.84)
Maryland	(673)	(746)	(445)	(557)	(1.18)	(0.81)	(0.82)	(0.84)	(1.43)
Massachusetts	(630)	(1,101)	(398)	(508)	(1.48)	(0.74)	(0.66)	(1.09)	(1.65)
Michigan	(246)	(600)	(140)	(204)	(1.08)	(0.41)	(0.39)	(0.85)	(1.16)
Minnesota	(381)	(825)	(257)	(360)	(1.22)	(0.59)	(0.52)	(0.86)	(1.35)
Mississippi	(680)	(755)	(322)	(433)	(2.27)	(1.15)	(1.32)	(1.41)	(2.55)
Missouri	(453)	(435)	(332)	(389)	(1.11)	(0.88)	(0.82)	(0.82)	(1.42)
Montana	(961)	(1,407)	(505)	(665)	(2.98)	(1.45)	(1.67)	(1.96)	(3.31)
Nebraska	(513)	(760)	(390)	(555)	(1.44)	(1.07)	(0.83)	(1.14)	(1.79)
Nevada	(638)	(860)	(432)	(577)	(1.69)	(1.13)	(0.93)	(1.33)	(2.04)
New Hampshire	(1,333)	(1,312)	(692)	(683)	(2.42)	(1.22)	(1.66)	(1.58)	(2.71)
New Jersey	(449)	(828)	(362)	(365)	(1.10)	(0.58)	(0.55)	(0.93)	(1.24)
New Mexico	(729)	(872)	(496)	(390)	(2.23)	(1.19)	(1.30)	(1.45)	(2.53)
New York	(399)	(349)	(208)	(290)	(0.74)	(0.47)	(0.55)	(0.47)	(0.88)
North Carolina	(422)	(395)	(269)	(357)	(1.03)	(0.77)	(0.66)	(0.74)	(1.28)
North Dakota	(1,686)	(1,654)	(793)	(771)	(3.63)	(1.63)	(2.53)	(2.11)	(3.98)
Ohio	(331)	(290)	(230)	(201)	(0.76)	(0.51)	(0.55)	(0.48)	(0.92)
Oklahoma	(327)	(549)	(221)	(342)	(1.17)	(0.73)	(0.61)	(0.97)	(1.38)
Oregon	(608)	(523)	(363)	(509)	(1.22)	(0.92)	(0.90)	(0.79)	(1.53)
Pennsylvania	(254)	(460)	(208)	(246)	(0.83)	(0.50)	(0.46)	(0.67)	(0.97)
Rhode Island	(1,059)	(1,809)	(849)	(1,020)	(2.98)	(1.81)	(1.59)	(2.04)	(3.48)
South Carolina	(509)	(717)	(284)	(436)	(1.57)	(0.91)	(0.88)	(1.20)	(1.82)
South Dakota	(958)	(1,098)	(629)	(535)	(2.46)	(1.37)	(1.56)	(1.47)	(2.81)
Tennessee	(389)	(548)	(268)	(305)	(1.21)	(0.70)	(0.62)	(0.92)	(1.40)
Texas	(287)	(437)	(142)	(167)	(0.82)	(0.33)	(0.41)	(0.60)	(0.89)
Utah	(647)	(847)	(384)	(662)	(1.42)	(1.00)	(0.82)	(1.14)	(1.73)
Vermont	(904)	(1,461)	(734)	(1,107)	(2.77)	(2.07)	(1.73)	(2.03)	(3.46)
Virginia	(548)	(517)	(461)	(418)	(1.00)	(0.81)	(0.70)	(0.60)	(1.29)
Washington	(539)	(625)	(399)	(327)	(1.05)	(0.65)	(0.65)	(0.74)	(1.24)
West Virginia	(739)	(717)	(408)	(538)	(2.11)	(1.37)	(1.36)	(1.45)	(2.51)
Wisconsin	(328)	(394)	(223)	(356)	(0.80)	(0.64)	(0.45)	(0.61)	(1.02)
Wyoming	(1,140)	(1,459)	(929)	(896)	(2.87)	(1.92)	(1.82)	(2.00)	(3.46)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit [2020 ACS 1-Year Experimental Data Tables (census.gov)](census.gov).
Notes: This table shows standard errors of the real median household income (in 2020 dollars, adjusted by the CPI-U-RS) by state. Point estimates associated with this table were shown in Table 3. Columns (1) and (2) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy balance weights. Columns (5) and (6) show the standard errors of the percent difference each year between the production and entropy balance weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and entropy balance weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).

Appendix Table 18: 75th Percentile of Real Household Income by State, Standard Errors

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	(127)	(118)	(73)	(110)	(0.15)	(0.11)	(0.12)	(0.11)	(0.19)
State									
Alabama	(812)	(834)	(564)	(623)	(1.26)	(0.88)	(0.77)	(0.97)	(1.54)
Alaska	(2,106)	(4,026)	(1,604)	(1,638)	(3.45)	(1.72)	(1.69)	(2.46)	(3.86)
Arizona	(556)	(1,294)	(398)	(427)	(1.32)	(0.53)	(0.57)	(1.05)	(1.42)
Arkansas	(943)	(977)	(567)	(646)	(1.62)	(0.99)	(0.98)	(1.03)	(1.90)
California	(386)	(382)	(299)	(415)	(0.39)	(0.35)	(0.31)	(0.31)	(0.52)
Colorado	(630)	(1,375)	(486)	(556)	(1.15)	(0.56)	(0.53)	(0.83)	(1.28)
Connecticut	(994)	(1,821)	(645)	(1,074)	(1.45)	(0.87)	(0.76)	(1.38)	(1.69)
Delaware	(2,177)	(1,951)	(1,135)	(1,065)	(2.43)	(1.26)	(1.67)	(1.60)	(2.74)
District of Columbia	(4,447)	(4,204)	(3,248)	(3,752)	(3.50)	(2.83)	(2.51)	(2.57)	(4.50)
Florida	(395)	(685)	(256)	(407)	(0.77)	(0.45)	(0.40)	(0.58)	(0.89)
Georgia	(763)	(925)	(449)	(683)	(1.13)	(0.74)	(0.66)	(0.81)	(1.35)
Hawaii	(1,791)	(2,186)	(753)	(1,307)	(2.08)	(1.06)	(1.29)	(1.51)	(2.33)
Idaho	(1,350)	(1,641)	(609)	(1,105)	(2.15)	(1.28)	(1.31)	(1.65)	(2.50)
Illinois	(393)	(673)	(274)	(641)	(0.64)	(0.56)	(0.35)	(0.58)	(0.85)
Indiana	(410)	(912)	(315)	(476)	(1.00)	(0.57)	(0.41)	(0.83)	(1.15)
Iowa	(595)	(920)	(412)	(661)	(1.07)	(0.76)	(0.62)	(0.82)	(1.32)
Kansas	(729)	(1,349)	(546)	(850)	(1.46)	(0.96)	(0.76)	(1.24)	(1.75)
Kentucky	(587)	(801)	(457)	(622)	(1.09)	(0.83)	(0.73)	(0.72)	(1.37)
Louisiana	(768)	(827)	(564)	(978)	(1.20)	(1.14)	(0.85)	(0.98)	(1.65)
Maine	(788)	(2,083)	(637)	(693)	(2.21)	(0.92)	(0.79)	(1.67)	(2.39)
Maryland	(760)	(976)	(506)	(422)	(0.85)	(0.45)	(0.53)	(0.64)	(0.96)
Massachusetts	(602)	(1,328)	(415)	(773)	(0.95)	(0.57)	(0.39)	(0.74)	(1.11)
Michigan	(389)	(875)	(253)	(397)	(0.94)	(0.45)	(0.34)	(0.67)	(1.04)
Minnesota	(559)	(919)	(379)	(467)	(0.87)	(0.49)	(0.35)	(0.67)	(1.00)
Mississippi	(896)	(949)	(607)	(774)	(1.63)	(1.16)	(1.00)	(1.17)	(2.00)
Missouri	(493)	(849)	(340)	(352)	(0.98)	(0.49)	(0.55)	(0.72)	(1.10)
Montana	(1,386)	(1,910)	(770)	(1,110)	(2.41)	(1.39)	(1.40)	(1.58)	(2.78)
Nebraska	(1,106)	(1,109)	(564)	(766)	(1.50)	(0.90)	(0.98)	(0.99)	(1.75)
Nevada	(772)	(1,192)	(520)	(600)	(1.32)	(0.73)	(0.62)	(1.01)	(1.51)
New Hampshire	(1,729)	(2,167)	(1,118)	(2,017)	(2.13)	(1.75)	(1.26)	(1.81)	(2.76)
New Jersey	(568)	(1,023)	(369)	(519)	(0.77)	(0.41)	(0.38)	(0.68)	(0.87)
New Mexico	(1,067)	(2,064)	(756)	(999)	(2.52)	(1.32)	(1.09)	(1.92)	(2.85)
New York	(438)	(615)	(369)	(400)	(0.57)	(0.39)	(0.37)	(0.40)	(0.69)
North Carolina	(403)	(675)	(312)	(455)	(0.78)	(0.54)	(0.40)	(0.60)	(0.95)
North Dakota	(1,619)	(1,902)	(1,250)	(1,822)	(2.28)	(1.98)	(1.60)	(1.82)	(3.02)
Ohio	(348)	(711)	(261)	(323)	(0.78)	(0.41)	(0.34)	(0.61)	(0.88)
Oklahoma	(706)	(690)	(397)	(408)	(1.05)	(0.58)	(0.73)	(0.65)	(1.20)
Oregon	(1,216)	(1,237)	(688)	(586)	(1.54)	(0.77)	(1.00)	(0.93)	(1.73)
Pennsylvania	(454)	(636)	(318)	(341)	(0.71)	(0.41)	(0.45)	(0.55)	(0.82)
Rhode Island	(1,574)	(2,353)	(1,067)	(1,807)	(2.39)	(1.70)	(1.38)	(1.80)	(2.93)
South Carolina	(663)	(1,235)	(462)	(457)	(1.41)	(0.65)	(0.67)	(1.16)	(1.55)
South Dakota	(1,208)	(1,272)	(715)	(1,448)	(1.74)	(1.59)	(1.16)	(1.36)	(2.35)
Tennessee	(628)	(532)	(402)	(565)	(0.85)	(0.69)	(0.67)	(0.55)	(1.10)
Texas	(430)	(402)	(305)	(327)	(0.53)	(0.38)	(0.43)	(0.38)	(0.65)
Utah	(721)	(1,116)	(452)	(673)	(1.11)	(0.67)	(0.60)	(0.86)	(1.30)
Vermont	(1,422)	(2,033)	(996)	(1,413)	(2.35)	(1.63)	(1.51)	(1.64)	(2.86)
Virginia	(984)	(648)	(706)	(529)	(0.90)	(0.65)	(0.66)	(0.45)	(1.11)
Washington	(707)	(1,011)	(556)	(753)	(0.93)	(0.69)	(0.54)	(0.62)	(1.16)
West Virginia	(1,167)	(1,716)	(611)	(877)	(2.40)	(1.22)	(1.19)	(1.63)	(2.69)
Wisconsin	(477)	(782)	(375)	(443)	(0.86)	(0.54)	(0.42)	(0.70)	(1.02)
Wyoming	(2,119)	(2,380)	(1,104)	(1,563)	(3.05)	(1.71)	(2.03)	(1.92)	(3.50)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Notes: This table shows standard errors of real household income at the 75th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Point estimates associated with this table were shown in Appendix Table 9. Columns (1) and (2) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the standard errors of the percent difference each year between the production and experimental weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and experimental weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).

Appendix Table 19: 90th Percentile of Real Household Income by State, Standard Errors

	Survey		EBW		Percent Difference (EBW-Survey)/Survey		Year-to-Year Change		Difference-in-Difference
	2019	2020	2019	2020	2019	2020	Survey	EBW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
National	(212)	(400)	(155)	(138)	(0.24)	(0.11)	(0.13)	(0.19)	(0.27)
State									
Alabama	(1,512)	(1,913)	(876)	(670)	(1.70)	(0.74)	(1.00)	(1.21)	(1.86)
Alaska	(4,204)	(3,360)	(2,146)	(2,097)	(2.68)	(1.51)	(2.03)	(1.85)	(3.08)
Arizona	(1,249)	(1,486)	(700)	(859)	(1.17)	(0.64)	(0.74)	(0.87)	(1.33)
Arkansas	(1,663)	(1,888)	(909)	(1,058)	(1.88)	(1.00)	(1.11)	(1.25)	(2.13)
California	(784)	(1,455)	(636)	(527)	(0.72)	(0.34)	(0.35)	(0.53)	(0.80)
Colorado	(921)	(2,105)	(774)	(1,116)	(1.13)	(0.66)	(0.47)	(0.85)	(1.31)
Connecticut	(1,855)	(3,232)	(1,602)	(2,344)	(1.61)	(1.21)	(0.95)	(1.60)	(2.02)
Delaware	(2,892)	(8,221)	(1,726)	(2,783)	(4.85)	(1.72)	(1.79)	(3.82)	(5.14)
District of Columbia									
Florida	(899)	(1,380)	(506)	(664)	(1.00)	(0.48)	(0.64)	(0.80)	(1.11)
Georgia	(1,379)	(1,903)	(865)	(1,008)	(1.36)	(0.75)	(0.75)	(0.98)	(1.55)
Hawaii	(1,961)	(6,720)	(1,631)	(2,672)	(3.39)	(1.44)	(1.15)	(2.89)	(3.68)
Idaho	(1,873)	(2,936)	(1,439)	(1,771)	(2.30)	(1.52)	(1.27)	(1.88)	(2.76)
Illinois	(1,036)	(1,736)	(791)	(791)	(1.06)	(0.57)	(0.63)	(0.85)	(1.20)
Indiana	(956)	(1,701)	(578)	(957)	(1.29)	(0.73)	(0.66)	(1.14)	(1.48)
Iowa	(1,327)	(1,601)	(840)	(1,129)	(1.36)	(0.92)	(0.90)	(1.00)	(1.64)
Kansas	(1,443)	(2,462)	(889)	(1,234)	(1.80)	(0.95)	(0.94)	(1.31)	(2.04)
Kentucky	(1,049)	(1,749)	(733)	(1,125)	(1.44)	(0.93)	(0.76)	(1.02)	(1.71)
Louisiana	(1,081)	(1,987)	(1,119)	(1,047)	(1.49)	(0.98)	(0.94)	(1.22)	(1.78)
Maine	(2,935)	(2,635)	(1,248)	(1,174)	(2.58)	(1.12)	(1.66)	(1.44)	(2.81)
Maryland	(1,389)	(1,962)	(1,160)	(877)	(1.04)	(0.62)	(0.63)	(0.83)	(1.21)
Massachusetts	(2,075)	(2,699)	(986)	(1,633)	(1.43)	(0.79)	(0.83)	(0.95)	(1.63)
Michigan	(1,152)	(1,548)	(372)	(808)	(1.21)	(0.55)	(0.66)	(0.82)	(1.33)
Minnesota	(940)	(1,912)	(761)	(696)	(1.14)	(0.56)	(0.53)	(0.98)	(1.27)
Mississippi	(1,107)	(2,478)	(1,209)	(1,269)	(2.05)	(1.29)	(1.08)	(1.70)	(2.42)
Missouri	(777)	(1,483)	(811)	(817)	(1.09)	(0.74)	(0.62)	(0.82)	(1.32)
Montana	(3,088)	(2,956)	(1,222)	(1,092)	(2.89)	(1.09)	(1.94)	(1.91)	(3.09)
Nebraska	(1,916)	(2,337)	(911)	(1,346)	(1.90)	(1.02)	(1.12)	(1.26)	(2.16)
Nevada	(2,063)	(2,574)	(1,055)	(1,651)	(2.02)	(1.17)	(1.32)	(1.50)	(2.34)
New Hampshire	(4,237)	(4,785)	(1,344)	(1,855)	(3.20)	(1.12)	(2.00)	(2.14)	(3.39)
New Jersey	(1,147)	(2,778)	(833)	(1,326)	(1.23)	(0.63)	(0.55)	(1.13)	(1.38)
New Mexico	(1,712)	(2,304)	(1,180)	(1,891)	(1.94)	(1.45)	(1.04)	(1.49)	(2.43)
New York	(1,290)	(1,644)	(674)	(818)	(0.95)	(0.46)	(0.63)	(0.64)	(1.05)
North Carolina	(1,139)	(1,798)	(445)	(749)	(1.34)	(0.54)	(0.65)	(1.03)	(1.44)
North Dakota	(4,738)	(4,319)	(2,690)	(2,442)	(3.86)	(2.19)	(2.89)	(2.60)	(4.44)
Ohio	(827)	(1,003)	(578)	(904)	(0.83)	(0.67)	(0.58)	(0.64)	(1.07)
Oklahoma	(1,125)	(2,023)	(768)	(808)	(1.56)	(0.73)	(0.76)	(1.27)	(1.73)
Oregon	(1,649)	(2,488)	(980)	(951)	(1.74)	(0.78)	(0.91)	(1.25)	(1.90)
Pennsylvania	(981)	(935)	(546)	(842)	(0.79)	(0.56)	(0.59)	(0.56)	(0.97)
Rhode Island	(3,160)	(6,858)	(1,575)	(3,460)	(4.22)	(1.96)	(1.93)	(3.21)	(4.65)
South Carolina	(1,000)	(1,700)	(646)	(1,262)	(1.25)	(0.89)	(0.61)	(1.21)	(1.53)
South Dakota	(1,704)	(2,269)	(1,508)	(1,555)	(1.88)	(1.46)	(1.28)	(1.40)	(2.38)
Tennessee	(858)	(2,126)	(927)	(1,115)	(1.49)	(0.93)	(0.67)	(1.20)	(1.76)
Texas	(746)	(920)	(535)	(528)	(0.66)	(0.40)	(0.45)	(0.51)	(0.77)
Utah	(1,929)	(1,992)	(926)	(1,062)	(1.57)	(0.77)	(1.11)	(1.04)	(1.75)
Vermont	(2,977)	(3,623)	(1,829)	(1,885)	(2.86)	(1.62)	(1.91)	(2.29)	(3.29)
Virginia	(1,485)	(1,780)	(924)	(1,205)	(1.07)	(0.69)	(0.70)	(0.83)	(1.27)
Washington	(1,588)	(2,016)	(1,000)	(1,585)	(1.23)	(0.89)	(0.72)	(0.86)	(1.51)
West Virginia	(1,374)	(2,883)	(984)	(1,538)	(2.41)	(1.35)	(0.94)	(1.99)	(2.76)
Wisconsin	(928)	(1,235)	(590)	(790)	(0.98)	(0.62)	(0.55)	(0.86)	(1.16)
Wyoming	(3,054)	(3,010)	(1,881)	(1,585)	(2.76)	(1.56)	(2.10)	(1.76)	(3.17)

Source: U.S. Census Bureau, 2019 and 2020 American Community Survey 1-year data. For more information on sampling and estimation methods, confidentiality protection, and sampling and nonsampling error, in the ACS, visit 2020 ACS 1-Year Experimental Data Tables (census.gov).
Notes: This table shows standard errors of real household income at the 90th percentile (in 2020 dollars, adjusted by the CPI-U-RS) by state. Point estimates associated with this table were shown in Appendix Table 10. Columns (1) and (2) show the standard errors in 2019 and 2020 respectively using the regular production weights. Columns (3) and (4) show the standard errors in 2019 and 2020 respectively using the experimental entropy-balance weights. Columns (5) and (6) show the standard errors of the percent difference each year between the production and experimental weights. Columns (7) and (8) show the standard errors of the year-to-year estimates for the production and experimental weights. Column (9) shows the standard errors of the difference between the year-to-year estimates in (7) and (8).