Evaluating Three Ways to Handle Drop Points in Address-Based Sampling Frame Surveys

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Abstract
Address-based sampling frames are commonly created from the U.S. Postal Service's Computerized Delivery Sequence (CDS) file, a comprehensive list of addresses in the US. While most addresses in the CDS represent only one household, some addresses--known as drop points (DPs)--are delivery points for two or more households. The drop point units (DPUs) therein do not have secondary unit designators specified in the CDS, which is a challenge for self-administered surveys since they cannot be contacted specifically. An earlier paper by the authors examined differences between responses of DPUs and nearby non-DPU substitutes in the 2021 Healthy Chicago Survey of sociodemographic characteristics and key health outcomes. This paper is a follow-up analysis comparing the effects of including, excluding, or substituting DPUs on the entire sampling frame, and thus entire study area, to quantify the magnitude of point estimate differences between those groups. No statistically significant differences were found in the distributions of sociodemographic or key health outcomes for the three groups. This is true even when focusing on the 11 community areas where more than 30% of the homes were DPUs.

Key Words: drop points, drop point addresses, ABS survey, health survey

1. Background

As random-digit dialing (RDD) has become less reliable due to its increasing nonresponse rates, using an address-based sampling (ABS) frame for household surveys has become more popular. ABS frames are created using the USPS Computerized Delivery Sequence file (CDS), which is a list of all addresses in the US that can receive mail. While most of the addresses in the CDS represent only one home or business, there are some addresses that receive mail for more than one household. These are known as drop points and the households within them are known as drop point units. Essentially, DPs serve as a single mail receptacle for all of the DPUs contained within them.

DPUs make up quite a small percentage of addresses in the CDS overall, only about 1.5 percent of all city-style or locatable addresses. The highest concentrations of DPs are in New York, New Jersey, Massachusetts, and Illinois, and mostly in urban areas. Figure 1 shows DPU concentration by county for all residential addresses on the ABS frame.

DPUs pose a specific challenge to self-administered, mail-contact surveys because there are no apartment numbers or secondary unit designators associated with them. Even though the number of DPUs contained in a DP is available on the CDS, it is impossible for practitioners to target mailings to specific DPUs to participate in a survey. In non-urban areas of the US, the proportion of DPs is small enough that to remove them would not raise any concerns of coverage bias. However, the decision to exclude drop points in urban areas where DP proportions are substantially higher may not be as easy to make. If drop points are kept eligible for the survey, there are several strategies that can be implemented, including sending just a single mailing to the DP or sending as many mailings as there are DPUs in the DP (Lewis et al. 2023b). While mailing to all DPUs in a DP yields marginally more completed surveys than a single mailing to a DP, they both present issues with potential self-selection bias. Naturally, excluding DPs could introduce coverage bias if the characteristics of residents in DPUs could differ from those living in non-DPUs.

An alternative to including or excluding DPUs would be to substitute them with nearby non-DPUs (Harter et al. 2022). Substitution can be used in a few different ways for surveys. One way is to use substitution as a form of imputation to make up for unit nonresponse (Nishimura 2015, Chapman 1983), by substituting a nonresponding case with a new case. While this form of substitution could be seen as a departure from pure probability-based sampling, it can be argued that if the distribution of characteristics of residents of nonresponding sampled housing units are comparable to those in substitute housing units, the technique could help minimize the risk of nonresponse bias. If this line of logic is followed, substitution could also be a viable option for minimizing coverage error if residents of DPUs and their non-DPU counterparts share similar distributions for key variables of interest in the study.

The 2021 Healthy Chicago Survey (HCS)—a self-administered, mail-contact survey—experimented with such a method of substitution. The HCS used an ABS frame that was comprised of over 12 percent DPUs, far above the national average, which makes finding a suitable method for dealing with DPUs imperative. Prior to drawing the sample, the ABS frame was expanded on DPs so that any of the DPUs within a DP could be selected individually, e.g. if there were three DPUs within a DP, the single record for the DP was replaced with three identical records representing the individual DPUs. To find suitable substitutes for the sampled DPUs after the sample was drawn, SAS software was used to deterministically find the closest non-DPU building with the same number of units as the DP. One of the units in the non-DPU building was then used as a substitute for the sampled DPU. To test the validity of this substitution approach, a concurrent survey was conducted using the DPUs that were originally sampled. Results discussed in Lewis et al. (2023b) were encouraging. There were some minor differences in sociodemographic characteristics, such as age, employment status, marital status, and housing tenure, but no substantive differences in key health outcomes.

The purpose of the present analysis is to determine the extent to which including, excluding, or substituting sampled DPUs affects the *overall* results of a survey. Specifically, our primary goal is to test for statistical significance of sociodemographic variables and key health outcomes between the three methods, with the secondary goal being to quantify the expected magnitude of any point estimate differences. To make these city-wide comparisons, three coverage- and nonresponse-adjusted analysis weights were created to make each group representative of the adult population of Chicago, per American Community Survey data. More details on the weighting procedures can be found in the Data and Methods section below.

This article is structured in the following way. In the Data and Methods section, more details are provided on the 2021 HCS and our methods of constructing the three aforementioned analysis weights. Then, data is presented on the outcome distributions and corresponding significance tests for comparing analysis-weighted respondent distributions for the three conditions. Finally, we summarize our findings, implications for researchers, and suggest paths for further exploration of ways to handle DPUs.

2. Data and Methods

The HCS commenced in 2014 as an annual, dual-frame (DF), RDD telephone survey of Chicago's adults as a way for the Chicago Department of Public Health to obtain information used to form policies addressing health inequality and to organize public health interventions. The results from this initial version of the survey were used to implement Healthy Chicago 2.0

(https://www.chicago.gov/city/en/depts/cdph/provdrs/healthychicago.html). Response rates gradually declined, which made getting the targeted number of completed surveys within the—sometimes small—77 community areas (CAs) of interest a challenge. The declining use of landline telephones and the portability of cellular telephones has made targeting specific geographies in DFRDD surveys increasingly difficult, i.e. a person's area code may not be representative of where the person lives (Berzofsky et al. 2018). In response to these challenges, the Chicago Department of Public Health moved the HCS to a self-administered, mail-contact survey using an ABS frame (Unangst et al. 2022).

The ABS frame used in the 2021 HCS Consisted of 1,207,642 addresses in all, 12.1 percent (146,711) of which were DPUs situated in DPs containing two to four units each. The other 1,060,931 were non-DPU addresses. A total of 10,871 DPUs were excluded from the 2021 HCS frame due to being in DPs that contained more than four units. This is because larger DPs are usually high-rises, trailer parks, gated communities, or other alternative housing arrangements such as college dormitories or halfway houses (Amaya et al. 2014) which can cause data collection logistical issues.

After geocoding addresses on the 2021 HCS frame, they were stratified into Chicago's CAs. As Figure 2 in Lewis et al. 2023a shows, DPUs are most concentrated in the "bungalow belt", a ring of CAs in Western Chicago. These CAs are less affluent and have higher density minority populations (Dekker et al. 2012). The prevalence of DPUs in CAs is not distributed homogeneously; some CAs have hardly any DPUs while some in the bungalow belt have a nearly 60 percent DPU rate.

The 2021 HCS started with a sample of 18,488 addresses with the goals of getting at least 35 complete surveys in each CA and 4,200 completes overall. The initial sample contained 2,196 DPUs which were then substituted with a non-DPU in a nearby non-DPU building of the same size as the DP. Physically, some substitutes look quite similar to the originally sampled DPU while other substitutes can appear very different. Figures 2a and 2b show two Google Street View pairings of DPUs and their non-DPU counterparts. Figure 2a shows a physically similar pairing while the pairing in Figure 2b is more dissimilar. Qualitative comparisons of DPUs and non-DPUs were conducted in the 2020 Residential Energy Consumption Survey (RECS), which implemented a similar substitution method on a national scale (Harter et al. 2022).

The GEODIST function in SAS was used to find the geographically closest non-DPU substitute for the sampled DPUs. The function calls in latitudinal and longitudinal coordinates of the sampled DPUs' addresses and finds the nearest appropriate non-DPU address by Euclidean distance, accounting for the Earth's curvature. Substitutes for the DPUs were found in the same CA every time, usually only 0.1 to 0.2 miles away. A substitute was at most about three city blocks away, or 0.3 miles. For 35 DPUs, the substitute selected was previously used or selected to serve as substitute for at least one other DPU. In this situation, the base weight of the substitute was adjusted (RTI International 2022). Otherwise, the base weight of the originally sampled DPU was used for the non-DPU substitute.

Unlike the previous analysis that was primarily concerned with the differences between the respondents living in DPUs and their substitutes, the authors wanted to analyze the effect of including, excluding, or substituting DPUs on the overall survey estimates after weighting the respondents to match distributions for all adults in the city of Chicago. Thus, in addition to the core analysis weight accounting for the substitution, as originally created and used for 2021 HCS analyses (see RTI International 2022 for more details), two new analysis weights were created using the same demographics of race, sex, age, marital status, education, and housing tenure from the 2015-2019 American Community Survey 5-year data tables. The first analysis weight created simulates the inclusion of DPs (i.e., no substitution), and the second analysis weight simulates the exclusion of DPs from the sampling frame (i.e., no DPs, no substitution). Three-way statistical significance tests of the weighted sociodemographic and key health outcomes were conducted using Rao-Scott design-adjusted chi-square tests (Rao et al. 1984). To accommodate the covariance in the chi-square tests caused by the overlapping non-DPU respondents in all three conditions, seven pseudo-PSUs were created within each CA and a data stacking approach was used (cf., Example 5.16 in Heeringa et al 2018) using SUDAAN's CROSSTAB procedure. In addition to testing for overall significance, we focused on the 11 CAs with DPUs making up at least 30 percent of their addresses to evaluate whether including, excluding, or substituting DPs affected areas with a higher proportion of DPUs led to differences of larger magnitude and/or greater statistical significance.

Note that the survey invitations for DPUs were mailed only once because there would be no guarantee that any follow-up correspondence would reach the intended recipient, i.e., the respondent of the survey, since there is no way to send mail to a specific DPU within a DP (Lewis et al. 2023a). The typical data collection protocol for non-DPU addresses is to send up to four mailings over a 28-day period.

3. Results

Table 1 shows the counts of cases and yield rates for the three conditions described above in the Data and Methods section. The yield rate is defined as the number of completed surveys divided by the number of sampled addresses, which is used as a measure of a successful survey response. It can be inferred from the slight increase of 1.8% in the yield rate when excluding DPs that there were proportionally fewer respondents from DPUs than non-DPUs (not including substitutes). Using substitutes from comparable non-DPUs instead of DPUs increased the yield rate 1.3%, indicating that the substitutes are somewhat more likely to respond than DPUs. For analysis purposes, it worked out nicely that the number of DPU respondents (399) and substitute respondents (401) were so close.

Table 2 contains the weighted percent distributions of sociodemographic characteristics of the three DP conditions for both the entire city and for only the 11 CAs which had 30 percent or more addresses being DPUs, along with indicators for which estimates were the median and maximum absolute value differences when comparing the three groups. None of the 10 sociodemographic distributions tested resulted in statistical significance for either the entire city or the 11 DPU-heavy CAs. The median differences in percentage distributions for the entire city were all less than one percentage point, as were the maximum differences. For the 11 CAs with the highest concentration of DPUs, the median difference was less than two percentage points, while the maximum differences neared nine percentage points in the categories of age (25-29 year-olds), households having kids, and having two adults in the household.

Table 3 shows the same comparisons, but for key health outcomes. As with the sociodemographic characteristics, none of the 17 key health outcomes had any statistically significant differences, even for the 11 CAs with the highest proportions of DPUs. The median differences for both the entire city and the 11 CAs with the most DPUs were comparable to those in the sociodemographic characteristics. The maximum differences for the entire city were a bit higher for the health outcomes than for the sociodemographic characteristics, but still were not higher than two percentage points.

4. Summary

This paper extended prior research conducted by the authors using data from the 2021 HCS that compared sociodemographic and key health outcome estimates from substitutes to their corresponding DPUs. Specifically, the current analysis evaluated the impact on city-wide estimates for the three methods for handling DPUs: excluding them from the survey, including them in the survey, or substituting them with nearby non-DPUs. Two additional analysis weights were created to simulate the first two conditions, using the same population benchmarks and methods as the official 2021 HCS weight, for which substitution was used. Only marginal differences were observed across the three methods, none of which were statistically significant.

We concluded analogous findings when restricting our analysis to the 11 CAs with at least 30 percent DPU concentration. The median percentage point differences between the distributions of the three groups were minimal for both sociodemographic characteristics and key health outcomes. Even though the maximum differences between the distributions of some groups were close to ten percentage points, they were not seen consistently for any given characteristic or outcome. These results indicate that the outcomes of the HCS would not be affected if DPs were excluded from the sample completely, which would be the simplest and most cost-effective method.

Aside from these findings in the Chicago area, it is unclear whether practitioners could remove DPs from all surveys in all areas of the US. Results may differ for other survey topics, or for surveys fielded in other urban areas or places with high DP concentrations. Performing similar concurrent data collection efforts of DPUs and non-DPU substitutes with other surveys in the US would provide valuable insights in this regard. Conducting a comparable concurrent data collection of DPUs in a much larger, perhaps nationwide, survey would be more informative as well, seeing as the sample sizes of 399 and 401 used in our study are relatively small. There is also much to be learned about how DPs are established and how the mail is distributed within; conducting a survey that is sent only to DPs with questions about this information and other characteristics of people living in DPUs could greatly inform researchers using ABS frames on decisions of if they should include, exclude, or substitute DPUs in their own surveys.

Disclaimer

The conclusions in this article are those of the authors and do not necessarily represent the views of the Chicago Department of Public Health.

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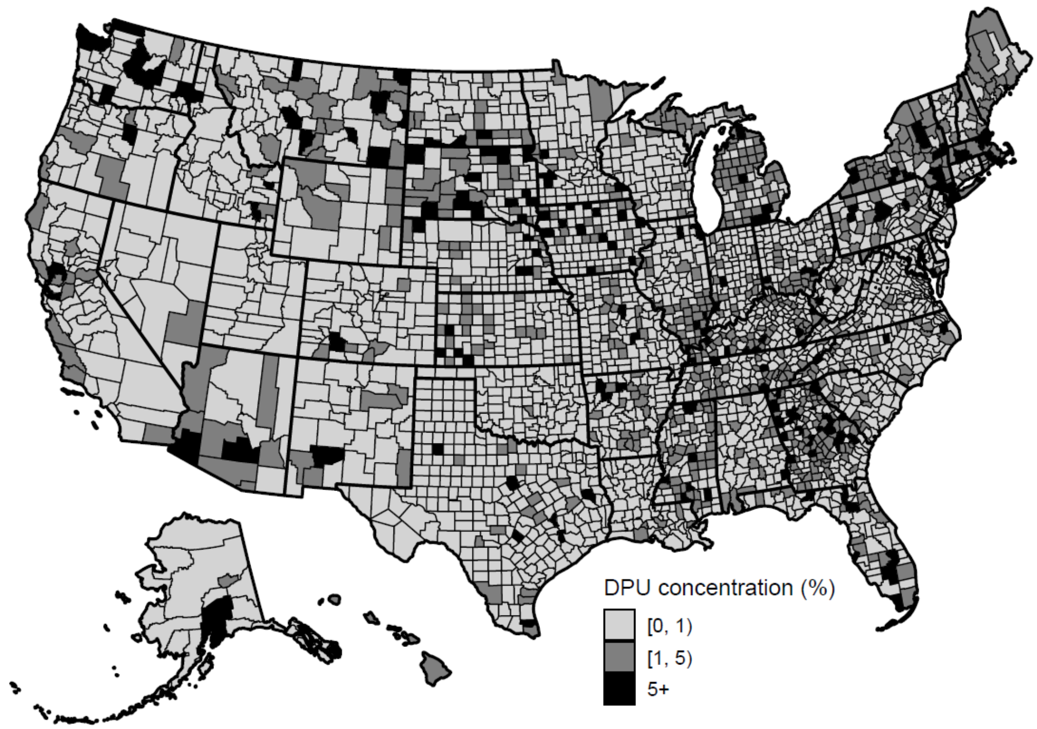

Figure 1. Drop point unit concentration of residential and PO box (only way to get mail) addresses by county in CDS, excluding educational addresses.

Figure 2. (A) Google Street View side-by-side images of a similar sampled drop point unit building (left) and substituted non-drop point unit building (right). (B) Google Street view side-by-side images of a less similar sampled drop point unit building (left) and substituted non-drop point unit building (right).

Table 1. Frame, Sample, and Complete Counts and Yield Rates for the Three Drop Point Conditions

Metric	Condition A: Including Drop Points	Condition B: Excluding Drop Points	Condition C: Substituting Drop Points
Addresses on Sampling Frame	1,354,353	1,207,642	1,354,353
Addresses Sampled	19,579	16,389	18,488
Number of Completes	4,235	3,836	4,237
Number of Completes excluding non-DPUs	399	NA	401
Yield Rate	21.6%	23.4%	22.9%

Table 2. Comparison of Sociodemographic Variable Distributions among Adults in City of Chicago in 2021 when Including, Excluding, and Substituting Drop Points

Distributions with Weighted Percents and Standard Errors, Median and Maximum Differences between groups

Variable	Entire City of Chicago				11 Community Areas with DPU Concentration of 30% or greater			
	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S
Age category								
18-24	13.5 (1.10)	13.3 (1.22)	13.0 (1.09)		22.3 (3.62)	22.1 (4.88)	19.4 (3.64)	
25-29	12.2 (0.86)	12.4 (0.89)	12.7 (0.85)		**5.7 (1.52)**	7.2 (2.20)	**11.3 (2.62)**	**Max I/S - 5.6**
30-44	29.7 (1.11)	29.7 (1.20)	29.6 (1.10)		32.6 (3.46)	31.7 (4.59)	30.9 (3.35)	
45-64	28.9 (1.07)	28.9 (1.17)	28.9 (1.06)		26.7 (3.13)	27.6 (4.47)	26.0 (3.29)	
65+	15.7 (0.71)	15.7 (0.82)	15.7 (0.76)		12.7 (1.90)	11.4 (2.87)	12.4 (2.39)	
Sex								
Male	48.0 (1.25)	48.2 (1.36)	48.2 (1.25)	Med I/E - 0.2	48.7 (3.80)	51.0 (5.21)	48.9 (3.96)	
Female	52.0 (1.25)	51.8 (1.36)	51.8 (1.25)		51.3 (3.80)	49.0 (5.21)	51.1 (3.96)	
Race-Ethnicity								
Non-Hispanic White	35.5 (1.07)	35.3 (1.14)	35.4 (1.06)		16.1 (2.38)	17.8 (3.20)	19.3 (2.69)	Med E/S - 1.5
Non-Hispanic Black	28.1 (1.19)	28.4 (1.25)	28.5 (1.18)		10.0 (1.95)	11.3 (2.81)	9.3 (2.06)	Med I/E - 1.3
Non-Hispanic Asian or Pacific Islander	6.1 (0.49)	6.3 (0.55)	6.2 (0.52)	Med I/S - 0.2	5.7 (1.75)	6.0 (2.13)	6.1 (1.73)	
Non-Hispanic Other or Multiple Races	3.2 (0.35)	3.0 (0.37)	3.1 (0.35)		2.3 (0.75)	2.5 (1.36)	2.3 (0.94)	
Hispanic/Latino	27.1 (1.23)	27.0 (1.39)	26.8 (1.23)		65.9 (3.30)	62.4 (4.52)	63.1 (3.56)	
Educational attainment								
Less than high school graduate	9.3 (0.84)	9.7 (0.99)	9.8 (0.88)		18.5 (3.29)	18.6 (4.53)	18.9 (3.35)	
High school graduate or equivalent	**28.3 (1.34)**	27.8 (1.45)	**27.6 (1.31)**	**Max I/S - 0.8**	41.1 (3.83)	40.9 (5.24)	40.9 (4.01)	
Some college or technical school	23.0 (0.98)	23.0 (1.06)	23.2 (0.99)		21.0 (2.56)	20.5 (3.50)	19.8 (2.60)	
College graduate	39.4 (1.09)	39.4 (1.19)	39.4 (1.09)		19.4 (2.21)	20.1 (3.00)	20.5 (2.50)	

Table 2. Comparison of Sociodemographic Variable Distributions among Adults in City of Chicago in 2021 when Including, Excluding, and Substituting Drop Points

Distributions with Weighted Percents and Standard Errors, Median and Maximum Differences between groups

Variable	Entire City of Chicago				11 Community Areas with DPU Concentration of 30% or greater			
	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S
Marital status								
Married	31.4 (1.08)	31.3 (1.19)	30.9 (1.07)		42.0 (3.61)	44.4 (4.97)	39.0 (3.71)	
Divorced or separated	9.9 (0.61)	10.1 (0.68)	10.0 (0.67)		6.8 (1.33)	7.5 (2.02)	7.8 (2.08)	
Widowed	5.0 (0.46)	5.0 (0.51)	5.0 (0.47)		3.3 (0.96)	3.7 (1.54)	3.8 (1.30)	
Never married	53.7 (1.21)	53.7 (1.31)	54.1 (1.21)		47.9 (3.77)	44.4 (5.02)	49.3 (3.92)	
Household tenure								
Owns home	49.2 (1.23)	49.5 (1.33)	49.2 (1.23)		48.9 (3.72)	50.5 (4.96)	48.2 (3.90)	
Rents or other arrangement	50.8 (1.23)	50.5 (1.33)	50.8 (1.23)		51.1 (3.72)	49.5 (4.96)	51.8 (3.90)	
Household has kids								
Yes	**32.3 (1.29)**	**31.4 (1.39)**	32.0 (1.29)	**Max I/E - 0.9**	45.5 (3.93)	**41.0 (5.11)**	**47.6 (4.07)**	**Max E/S - 6.6**
No	67.7 (1.29)	68.6 (1.39)	68.0 (1.29)		54.5 (3.93)	59.0 (5.11)	52.4 (4.07)	
Employment status								
Employed for wages	52.3 (1.24)	52.4 (1.35)	52.3 (1.24)		51.0 (3.73)	48.4 (4.96)	53.0 (3.90)	
Self-employed	7.2 (0.70)	7.1 (0.73)	7.6 (0.71)		5.5 (1.66)	4.8 (1.79)	6.7 (1.80)	Med I/S - 1.2
Out of work for 1 year or more	5.5 (0.61)	5.0 (0.58)	5.1 (0.58)		6.0 (1.73)	5.4 (1.84)	4.9 (1.48)	
Out of work for less than 1 year	3.1 (0.49)	3.5 (0.66)	3.4 (0.53)		2.3 (1.19)	4.6 (3.49)	1.8 (1.20)	
Homemaker	3.9 (0.48)	3.4 (0.46)	3.4 (0.41)		7.3 (1.85)	4.9 (1.41)	5.6 (1.41)	
Student	6.5 (0.75)	6.9 (0.92)	6.6 (0.79)		6.5 (2.30)	11.2 (4.44)	9.2 (2.93)	
Retired	14.7 (0.72)	14.9 (0.83)	14.8 (0.76)	Med E/S - 0.1	10.8 (1.88)	11.1 (3.02)	10.4 (2.23)	
Unable to work	6.8 (0.72)	6.7 (0.74)	6.7 (0.71)		10.6 (2.72)	9.7 (2.82)	8.4 (2.38)	

Table 2. Comparison of Sociodemographic Variable Distributions among Adults in City of Chicago in 2021 when Including, Excluding, and Substituting Drop Points

Distributions with Weighted Percents and Standard Errors, Median and Maximum Differences between groups

Variable	Entire City of Chicago				11 Community Areas with DPU Concentration of 30% or greater			
	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S
Sexual identity								
Heterosexual or straight	86.6 (0.84)	86.5 (0.88)	86.9 (0.81)		90.6 (2.06)	88.5 (2.94)	88.2 (2.44)	
Gay or lesbian	4.9 (0.44)	5.2 (0.50)	4.9 (0.43)		2.0 (0.94)	2.2 (1.49)	2.1 (1.01)	
Bisexual	5.6 (0.62)	5.7 (0.65)	5.5 (0.59)		5.3 (1.63)	6.4 (2.16)	5.8 (1.78)	
Other/e	2.9 (0.43)	2.6 (0.42)	2.7 (0.42)		2.1 (0.94)	2.8 (1.52)	3.9 (1.49)	
Adults in Household								
1	29.6 (1.11)	29.7 (1.16)	29.4 (1.08)		14.4 (2.31)	16.8 (3.23)	18.7 (2.89)	
2	41.6 (1.25)	**40.9 (1.35)**	**41.7 (1.24)**	**Max E/S - 0.8**	**39.2 (3.77)**	**33.6 (4.66)**	37.3 (3.80)	**Max I/E - 8.7**
3+	28.8 (1.28)	29.4 (1.50)	28.9 (1.32)		46.3 (3.94)	49.6 (5.41)	44.0 (4.12)	

Estimates may appear off due to rounding

Table 3. Comparison of Key Health Outcomes Distributions among Adults in City of Chicago in 2021 when Including, Excluding, and Substituting Drop Points Distributions with Weighted Percents and Standard Errors, Median and Maximum Differences between groups

Variable	Entire City of Chicago				11 Community Areas with DPU Concentration of 30% or greater			
	Including Drop Points (I)	**Excluding Drop Points (E)**	**Substituting Drop Points (S)**	**Median or Maximum difference between I/E/S**	**Including Drop Points (I)**	**Excluding Drop Points (E)**	**Substituting Drop Points (S)**	**Median or Maximum difference between I/E/S**
Overall health status								
Excellent, very good, or good	87.9 (0.85)	87.6 (1.01)	88.0 (0.84)	Med I/E - 0.3	85.3 (2.63)	84.0 (4.39)	88.0 (2.50)	
Fair or poor	12.1 (0.85)	12.4 (1.01)	12.0 (0.84)		14.7 (2.63)	16.0 (4.39)	12.0 (2.50)	
Has primary health care provider								
Yes	81.3 (1.00)	81.4 (1.13)	81.7 (1.00)		73.5 (3.35)	74.6 (4.64)	74.8 (3.42)	
No	18.7 (1.00)	18.6 (1.13)	18.3 (1.00)	Med I/S - 0.4	26.5 (3.35)	25.4 (4.64)	25.2 (3.42)	
Had routine health checkup in past year								
Yes	74.3 (1.06)	74.4 (1.18)	74.4 (1.07)		73.4 (3.23)	70.5 (4.88)	71.2 (3.56)	
No	25.7 (1.06)	25.6 (1.18)	25.6 (1.07)		26.6 (3.23)	29.5 (4.88)	28.8 (3.56)	
Received needed care in past year								
Never	3.2 (0.60)	3.3 (0.60)	3.4 (0.63)		4.7 (1.90)	4.4 (2.09)	5.4 (2.52)	
Sometimes	19.8 (1.21)	19.1 (1.21)	19.2 (1.14)		26.6 (4.27)	18.3 (4.09)	26.4 (4.29)	
Usually or always	76.9 (1.28)	77.6 (1.29)	77.4 (1.23)		**68.7 (4.42)**	**77.3 (4.52)**	**68.2 (4.59)**	**Max I/E - 8.7** **Max E/S - 9.1**
Satisfied with health care received in past year								
Very satisfied	58.1 (1.28)	58.7 (1.38)	58.8 (1.26)		55.3 (3.91)	54.4 (5.21)	54.5 (4.10)	
Somewhat satisfied	37.4 (1.25)	37.0 (1.35)	37.4 (1.24)		38.1 (3.77)	40.1 (5.13)	41.5 (4.05)	
Not at all satisfied	4.5 (0.60)	4.2 (0.61)	3.9 (0.54)		6.6 (2.08)	5.5 (2.25)	4.0 (1.42)	
Had teeth cleaned in past year								
Yes	57.8 (1.23)	57.7 (1.34)	57.7 (1.23)		54.6 (3.68)	56.0 (5.02)	52.2 (3.89)	
No	42.2 (1.23)	42.3 (1.34)	42.3 (1.23)		45.4 (3.68)	44.0 (5.02)	47.8 (3.89)	
Ever diagnosed with high blood pressure								
Yes	29.2 (1.09)	**29.2 (1.18)**	**30.3 (1.13)**	**Max E/S - 1.1**	25.3 (3.03)	24.8 (4.04)	23.8 (3.29)	
No	70.8 (1.09)	70.8 (1.18)	69.7 (1.13)		74.7 (3.03)	75.2 (4.04)	76.2 (3.29)	Med E/S - 1.1

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Variable	Entire City of Chicago				11 Community Areas with DPU Concentration of 30% or greater			
	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S
Currently have asthma								
Yes	8.0 (0.62)	8.6 (0.81)	7.8 (0.66)		5.1 (1.37)	6.8 (3.44)	4.6 (2.02)	Med I/E - 1.7
No	92.0 (0.62)	91.4 (0.81)	92.2 (0.66)		94.9 (1.37)	93.2 (3.44)	95.4 (2.02)	
Ever diagnosed with diabetes								
Yes	11.7 (0.79)	12.4 (1.00)	12.4 (0.86)		15.4 (2.51)	17.7 (4.47)	13.2 (2.50)	
No	88.3 (0.79)	87.6 (1.00)	87.6 (0.86)		84.6 (2.51)	82.3 (4.47)	86.8 (2.50)	
Smoking status								
Current smoker	10.2 (0.72)	10.1 (0.80)	10.5 (0.77)		8.0 (1.59)	8.0 (2.31)	7.3 (1.87)	
Former smoker	17.2 (0.83)	18.3 (0.94)	18.0 (0.86)	Max E/S - 0.3	11.5 (2.23)	15.0 (3.27)	13.3 (2.29)	Med I/S - 1.7
Never smoked	72.6 (1.03)	71.6 (1.15)	71.5 (1.07)		80.5 (2.65)	77.0 (3.87)	79.4 (2.84)	
Number of servings of fruits/vegetables yesterday								
0 servings	8.0 (0.83)	7.8 (0.83)	7.9 (0.77)		11.7 (2.44)	11.1 (2.90)	9.7 (2.04)	
1-4 servings	59.0 (1.23)	59.6 (1.32)	59.1 (1.22)		55.8 (3.80)	59.5 (5.00)	60.1 (3.85)	
5+ servings	33.1 (1.14)	32.5 (1.24)	33.0 (1.15)		32.5 (3.71)	29.5 (4.66)	30.2 (3.69)	
Experienced psychological distress in past 30 days								
No distress	72.4 (1.14)	72.2 (1.25)	72.9 (1.13)		76.0 (3.10)	76.9 (4.27)	76.0 (3.34)	
Mild or moderate distress	16.9 (0.92)	17.4 (1.05)	17.5 (0.96)		12.7 (2.36)	15.2 (3.81)	15.8 (2.86)	
Serious distress	10.7 (0.86)	10.4 (0.89)	9.6 (0.79)		11.3 (2.32)	7.9 (2.45)	8.2 (2.14)	
Misused prescription opiates in past year								
Yes	2.9 (0.50)	3.0 (0.53)	3.2 (0.50)		2.1 (0.82)	3.0 (1.45)	3.8 (1.46)	
No	97.1 (0.50)	97.0 (0.53)	96.8 (0.50)		97.9 (0.82)	97.0 (1.45)	96.2 (1.46)	

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Variable	Entire City of Chicago				11 Community Areas with DPU Concentration of 30% or greater			
	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S	Including Drop Points (I)	Excluding Drop Points (E)	Substituting Drop Points (S)	Median or Maximum difference between I/E/S
Feels safe in the neighborhood								
Yes, all or most of the time	60.9 (1.24)	60.3 (1.38)	60.7 (1.24)		51.5 (3.69)	50.1 (5.09)	50.2 (3.90)	
Sometimes	**28.3 (1.15)**	**29.9 (1.34)**	28.8 (1.17)	**Max I/E - 1.6**	34.6 (3.45)	41.1 (5.26)	37.4 (3.81)	
No, or mostly no	10.8 (0.85)	9.8 (0.88)	10.5 (0.84)		13.9 (2.33)	8.8 (2.14)	12.4 (2.56)	
I really feel part of my neighborhood								
Strongly agree or agree	**41.9 (1.20)**	42.2 (1.31)	**43.2 (1.21)**	**Max I/S - 1.3**	43.9 (3.74)	42.9 (5.01)	42.3 (3.87)	
Neutral, disagree, or strongly disagree	58.1 (1.20)	57.8 (1.31)	56.8 (1.21)		56.1 (3.74)	57.1 (5.01)	57.7 (3.87)	
Has difficulty getting fresh produce								
Yes	13.2 (0.94)	12.2 (0.92)	12.1 (0.85)		**18.7 (3.09)**	14.1 (3.12)	**14.3 (2.72)**	**Max I/S - 4.4**
No	86.8 (0.94)	87.8 (0.92)	87.9 (0.85)		81.3 (3.09)	85.9 (3.12)	85.7 (2.72)	
Exercised in past month								
Yes	76.7 (1.07)	75.7 (1.22)	75.9 (1.09)		68.8 (3.35)	63.4 (5.15)	66.3 (3.72)	
No	23.3 (1.07)	24.3 (1.22)	24.1 (1.09)		31.2 (3.35)	36.6 (5.15)	33.7 (3.72)	

Estimates may appear off due to rounding