



July 2020

HOMELESSNESS

Better HUD Oversight of Data Collection Could Improve Estimates of Homeless Population

Accessible Version

GAO Highlights

Highlights of [GAO-20-433](#), a report to the Chairwoman, Committee on Financial Services, House of Representatives

July 2020

Homelessness

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Why GAO Did This Study

Policymakers have raised concerns about the extent to which recent increases in homelessness are associated with the availability of affordable housing. Moreover, counting the homeless population is a longstanding challenge. GAO was asked to review the current state of homelessness in the United States. This report examines (1) efforts to measure homelessness and HUD's oversight of these efforts and (2) factors associated with recent changes in homelessness.

GAO analyzed three HUD data sources on homelessness and developed an econometric model of the factors influencing changes in homelessness. GAO also conducted structured interviews with 12 researchers and representatives of 21 CoCs and four focus groups with a total of 34 CoC representatives responsible for collecting and maintaining homelessness data. CoCs were selected for interviews and focus groups to achieve diversity in size and geography. GAO also visited three major cities that experienced recent increases in homelessness.

What GAO Recommends

GAO recommends that HUD (1) conduct quality checks on CoCs' data-collection methodologies, (2) improve its instructions for using probability sampling techniques to estimate homelessness, and (3) assess and enhance the assistance it provides to CoCs on data collection. HUD concurred with the recommendations.

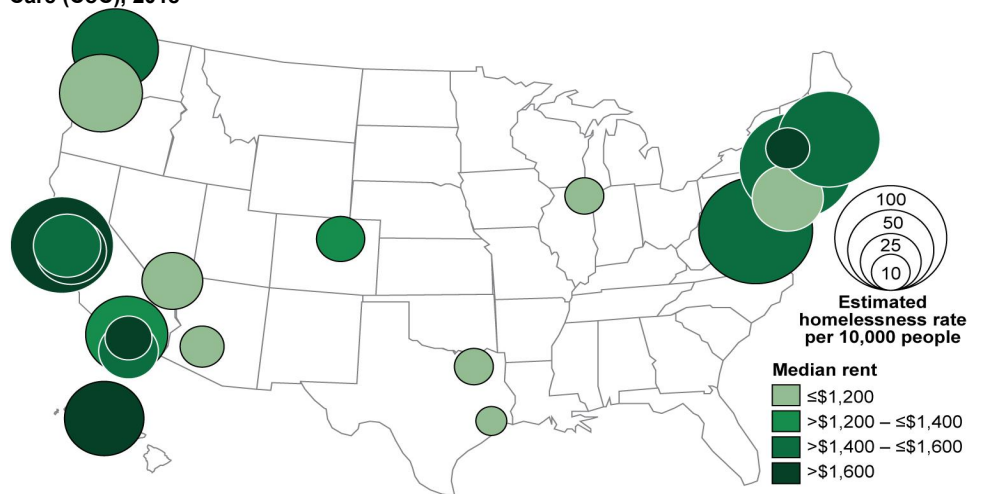
View [GAO-20-433](#). For more information, contact Alicia Puente Cackley at (202) 512-8678 or cackleya@gao.gov.

What GAO Found

Data collected through the Point-in-Time (PIT) count—a count of people experiencing homelessness on a single night—have limitations for measuring homelessness. The PIT count is conducted each January by Continuums of Care (CoC)—local homelessness planning bodies that apply for grants from the Department of Housing and Urban Development (HUD) and coordinate homelessness services. The 2019 PIT count estimated that nearly 568,000 people (0.2 percent of the U.S. population) were homeless, a decline from the 2012 count of about 621,500 but a slight increase over the period's low of about 550,000 in 2016. While HUD has taken steps to improve data quality, the data likely underestimate the size of the homeless population because identifying people experiencing homelessness is inherently difficult. Some CoCs' total and unsheltered PIT counts have large year-over-year fluctuations, which raise questions about data accuracy. GAO found that HUD does not closely examine CoCs' methodologies for collecting data to ensure they meet HUD's standards. HUD's instructions to CoCs on probability sampling techniques to estimate homelessness were incomplete. Some CoC representatives also said that the assistance HUD provides on data collection does not always meet their needs. By strengthening its oversight and guidance in these areas, HUD could further improve the quality of homelessness data.

To understand factors associated with homelessness in recent years, GAO used PIT count data to conduct an econometric analysis, which found that rental prices were associated with homelessness. To mitigate data limitations, GAO used data from years with improved data quality and took other analytical steps to increase confidence in the results. CoC representatives GAO interviewed also identified rental prices and other factors such as job loss as contributing to homelessness.

Estimated Homelessness Rates and Household Median Rent in the 20 Largest Continuums of Care (CoC), 2018



Source: GAO analysis of Department of Housing and Urban Development and U.S. Census Bureau data. | GAO-20-433

Data Table for Estimated Homelessness Rates and Household Median Rent in the 20 Largest Continuums of Care (CoC), 2018

Rank	CoC Number	CoC Name	2018 PIT Count (What We Used to Select Top 20)	2018 Median Rent (Used for Shading of Bubble)	Estimated Homelessness Rate per 10,000 People (Used for Bubble Diameter)
1	NY-600	New York City CoC	78,676	1409	94
2	CA-600	Los Angeles City & County CoC	49,955	1354	49
3	WA-500	Seattle/King County CoC	12,112	1413	54
4	CA-601	San Diego City and County CoC	8,576	1503	26
5	CA-500	San Jose/Santa Clara City & County CoC	7,254	2003	37
6	DC-500	District of Columbia CoC	6,904	1459	98
7	CA-501	San Francisco CoC	6,857	1751	78
8	AZ-502	Phoenix, Mesa/Maricopa County CoC	6,298	1058	14
9	MA-500	Boston CoC	6,188	1454	77
10	NV-500	Las Vegas/Clark County CoC	6,083	1074	27
11	PA-500	Philadelphia CoC	5,788	994	37
12	CA-502	Oakland, Berkeley/Alameda County CoC	5,496	1585	33
13	IL-510	Chicago CoC	5,450	1069	11
14	CO-503	Metropolitan Denver CoC	5,317	1275	17
15	CA-602	Santa Ana, Anaheim/Orange County CoC	4,955	1734	16
16	HI-501	Honolulu City and County CoC	4,495	1693	46
17	TX-700	Houston, Pasadena, Conroe/Harris, Ft. Bend, Montgomery, Counties CoC	4,143	1056	7
18	TX-600	Dallas City & County, Irving CoC	4,121	1075	11
19	OR-501	Portland, Gresham/Multnomah County CoC	4,019	1121	50
20	NY-603	Nassau, Suffolk Counties CoC	3,868	1694	14

Note: This map shows the 20 largest Point-in-Time counts by CoC in 2018. GAO estimated 2018 homelessness rates because the U.S. Census Bureau data used to calculate these rates were available up to 2018 at the time of analysis. GAO used 2017 median rents (in 2018 dollars) across all unit sizes and types.

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Abbreviations

ACS	American Community Survey
CoC	Continuum of Care
Education	Department of Education
EHCY	Education for Homeless Children and Youth
HMIS	Homeless Management Information System
HOMES	Homeless Operations Management and Evaluation System
HUD	Department of Housing and Urban Development
OESE	Office of Elementary and Secondary Education
PIT count	Point-in-Time count
SNAP	Supplemental Nutrition Assistance Program
USICH	U.S. Interagency Council on Homelessness
VA	Department of Veterans Affairs

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Letter

July 14, 2020

The Honorable Maxine Waters
Chairwoman
Committee on Financial Services
House of Representatives

Dear Chairwoman,

In 2019, the estimated count of the homeless population in the United States grew for the third consecutive year. The Department of Housing and Urban Development (HUD) found that national increases during the last 3 years (2017–2019) were driven by significant regional increases in homelessness in metropolitan areas, such as Los Angeles and New York. Policymakers have raised concerns about the progress being made to prevent and end homelessness and the extent to which recent increases in homelessness are associated with the availability of affordable housing and rental costs. Moreover, counting the homeless population is a longstanding challenge.

You asked us to review the current state of homelessness in the United States, including the methods used to determine the number of people experiencing homelessness and the factors influencing recent increases in homelessness counts in certain locations, such as coastal cities.¹ This report examines (1) efforts to measure homelessness and HUD's oversight of these efforts and (2) factors related to recent changes in homelessness.

To address both objectives, we identified and reviewed federal efforts to collect data on homelessness and interviewed officials from the federal agencies responsible for those efforts. We met with officials of the U.S. Interagency Council on Homelessness (USICH) to discuss homelessness

¹Coastal cities with the largest homeless populations in the United States include Los Angeles, California, and New York, New York. Cities in coastal states with increasing levels of homelessness in recent years include Los Angeles, California; San Francisco, California; New York, New York; and Seattle, Washington.

assistance programs and data across its 19 federal member agencies.² We also reviewed relevant federal guidance and literature. To assess the quality of HUD's data on homelessness, we conducted electronic testing on three HUD data sources and conducted four focus groups with a total of 34 representatives from across the country responsible for collecting and maintaining homelessness data in their localities.³ Focus groups were designed to capture the experience of localities using each HUD data source. Participants were selected to achieve diversity in the localities' geographic size and region and data collection methods, as well as the methodology used for the Point-in-Time (PIT) count of the homeless population.⁴

To further evaluate the quality of the data, we conducted structured interviews with 12 researchers with experience using HUD data sources for analysis. We determined that the PIT count data did not provide a reliably precise estimate of the homeless population. However, we determined that the data were sufficiently reliable for our purposes of conducting trend and econometric analyses (discussed below) once we applied a number of statistical techniques and controlled for certain variables. For example, we performed sensitivity analyses, including removing localities with unusual changes in year-to-year counts. We assessed HUD guidance and oversight of homelessness data collection against HUD's Point-in-Time Count Methodology Guide, HUD's Continuum of Care program interim rule, federal internal control standards, and federal standards for statistical surveys.⁵ See appendix II

²USICH member agencies are the Departments of Agriculture, Commerce, Defense, Education, Energy, Health and Human Services, Homeland Security, Housing and Urban Development, Interior, Justice, Labor, Transportation, and Veterans Affairs, as well as the Corporation for National and Community Service, General Services Administration, Office of Management and Budget, Social Security Administration, U.S. Postal Service, and White House Faith and Opportunity Initiative.

³See app. I for more detail on the specific federal data sources we reviewed.

⁴As discussed in detail below, the PIT count is a count of sheltered and unsheltered people experiencing homelessness on a single night in January.

⁵GAO, *Standards for Internal Control in the Federal Government*, [GAO-14-704G](#) (Washington, D.C.: Sept. 10, 2014). Office of Management and Budget, *Standards and Guidelines for Statistical Surveys* (Washington, D.C.: 2006). 24 C.F.R. Part 578.

for a detailed discussion of our treatment of the data and sensitivity analyses.⁶

To understand the factors related to changes in homelessness counts in recent years, we conducted multiple regression analyses using data from the PIT count and the U.S. Census Bureau's American Community Survey from 2012 through 2018, among other sources discussed in appendix II.⁷ We included variables from the American Community Survey on a variety of local factors, including housing and economic factors and demographic characteristics; from the National Oceanic and Atmospheric Administration, including weather; and from HUD, including federal funding. We interviewed representatives of 21 localities about the factors contributing to changes in homelessness. These localities were selected to reflect a range of geographic areas and sizes. Additionally, because recent studies identified metropolitan areas as driving increases in homelessness, we visited local officials and homeless service providers in three major cities (Colorado Springs, Los Angeles, and New York) that experienced increases in homelessness from 2012 through 2018.⁸ We also conducted literature searches to identify studies or reports related to homelessness data collection and factors affecting homelessness levels.

Appendix I provides more information on our scope and methodology. Appendix II provides a detailed discussion of the econometric analysis we conducted to better understand the factors that appear to have influenced recent changes in homelessness counts, including the limitations associated with our approach. Finally, appendix III provides an overview of data on homelessness collected by the Departments of Education and Veterans Affairs.

⁶HUD officials told us that the reliability of PIT count data has improved over time, and our analysis also found fewer anomalous values in more recent PIT counts, which we discuss later in this report. As a result, we excluded data from the early years of the PIT count from our analysis. In particular, we used 2012–2019 data and excluded 2007–2011 data. We also applied statistical techniques, such as controlling for weather, which might affect the counts. We performed other sensitivity analyses to increase our confidence in the results. For example, we removed localities with unusual changes in year-to-year counts and controlled for available information on the methodology used for counting.

⁷Although data from the 2019 PIT count were released in January 2020, data from HUD's 2018 PIT count were the most recent available at the time we began the process of conducting our econometric analysis.

⁸In app. II we discuss recent studies associated with changing levels of homelessness. At the time of our site visit selection, 2018 PIT count data were the most recent available.

We conducted this performance audit from March 2018 to July 2020 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Background

Multiple federal agencies administer programs designed to address the needs of those experiencing homelessness. The U.S. Interagency Council on Homelessness (USICH) is statutorily charged with developing a national strategic plan to end homelessness and updating it annually. As previously discussed, USICH comprises 19 federal member agencies involved in efforts to prevent and end homelessness, including HUD and the Departments of Health and Human Services, Education, Labor, and Veterans Affairs, among others. Several USICH members collect program data on subpopulations experiencing homelessness, but HUD is the only agency that collects data to provide annual estimates of the number of people experiencing homelessness in the United States.

HUD must use the McKinney-Vento Act definition of homelessness, which defines a homeless individual in part as someone who lacks a fixed, regular, and adequate nighttime residence.⁹ HUD has interpreted the McKinney-Vento Act definition, for inclusion in HUD's data collection, to include individuals who reside in places not meant for human habitation,

⁹42 U.S.C. § 11302(a). The residence can be a supervised shelter designed to provide temporary accommodations; an institution providing a temporary residence for individuals awaiting institutionalization; or a place not designed for, nor ordinarily used as, a regular sleeping accommodation. Additionally, HUD considers individuals homeless if they are being evicted within a week from a private dwelling and no subsequent residence has been identified and the person lacks the resources and support networks needed to obtain housing; are being discharged within a week from an institution in which they have been a resident for 30 or more consecutive days and no subsequent residence has been identified; or are fleeing a domestic violence situation.

such as cars, abandoned buildings, condemned housing, or on the street; or in an emergency shelter, transitional housing, or safe haven project.¹⁰

HUD's data collection efforts are built into its Continuum of Care (CoC) program—a grant program designed to help communities assist individuals (including unaccompanied youth) and homeless families.¹¹ A CoC is a regional or local planning body that coordinates homeless response funding, provides homelessness services, and applies for CoC program grants in a geographic area.¹² As of January 2020, there were 397 CoCs that covered virtually the entire United States. Some CoCs encompass populous urban areas and major cities. Others include multiple cities and surrounding counties, and some cover wider areas of a state. CoCs range in size and population density.¹³ CoCs are also responsible for planning homelessness services, setting local priorities, and collecting and reporting homelessness data. HUD awards grants annually to help CoCs improve coordination and integration of services within their communities and improve performance measurement.

HUD has three primary data sources it uses to estimate the size of the U.S. homeless population: the PIT count, Housing Inventory Count, and

¹⁰A safe haven is a form of supportive housing that serves hard-to-reach homeless persons with severe mental illness who come primarily from the streets and have been unable or unwilling to participate in housing or supportive services.

¹¹The Homeless Emergency Assistance and Rapid Transition to Housing Act of 2009 (HEARTH Act) amended the McKinney-Vento Homeless Assistance Act. Among other changes, the HEARTH Act consolidated the three separate McKinney-Vento homeless assistance programs (the Supportive Housing, Shelter Plus Care, and Section 8 Moderate Rehabilitation Single Room Occupancy programs) into a single grant program known as the Continuum of Care (CoC) program. Additionally, the CoC program interim rule, 24 CFR Part 578, governs the CoC grant program.

¹²The CoC may comprise representatives of organizations, including nonprofit homeless providers, victim service providers, faith-based organizations, governments, businesses, advocates, public housing agencies, school districts, social service providers, mental health agencies, hospitals, universities, affordable housing developers, law enforcement, organizations that serve homeless and formerly homeless veterans, and homeless and formerly homeless persons to the extent these groups are represented within the geographic area and are available to participate.

¹³State-based CoCs include “balance of state” CoCs, which comprise all jurisdictions in a state that are not covered by any other CoC, including nonmetropolitan areas, and may include some or all of the state's smaller cities. A statewide CoC covers every jurisdiction in the state. For example, South Dakota Statewide CoC is classified as rural and covers the full geography of the state; it had a relatively low homelessness count in 2019 of 995.

Homeless Management Information System (HMIS) databases.¹⁴ Under the McKinney-Vento Act, HUD is to develop an estimate of homeless persons in sheltered and unsheltered locations at a 1-day point in time. To do so, HUD requires CoCs to conduct counts of sheltered individuals (those in emergency shelters, transitional housing programs, or safe haven projects) and unsheltered individuals (those on the street or in other places not suitable for human habitation) at least every 2 years.¹⁵ In the annual Housing Inventory Count, which is conducted at the same time as the PIT count, CoCs provide information on the number of units and beds dedicated to housing homeless or formerly homeless persons within the CoC. CoCs are also required to collect and maintain client-level data in an HMIS database throughout the year. See table 1 for information on these data sources.

Table 1: HUD Homeless Data Sources

Data source	Data collected	Frequency of data collection
Point-in-Time Count	Sheltered and unsheltered individuals on night of count	Every 2 years ^a
Housing Inventory Count	Bed inventory by type on night of the count (emergency shelter, transitional housing, safe haven, and permanent housing, such as permanent supportive housing, and rapid rehousing)	Annual
Homeless Management Information System	Client, service, and housing data for individuals and families who are homeless and at risk of homelessness	Continuous (submitted to HUD annually)

Source: Department of Housing and Urban Development (HUD). | GAO-20-433

^aHUD requires Continuums of Care (CoC) to conduct a sheltered and unsheltered count every 2 years but through its CoC funding process incentivizes annual counts. All CoCs conduct annual sheltered counts and most CoCs conduct unsheltered Point-in-Time counts every year. HUD data show that, on average, 84 percent of CoCs conducted unsheltered counts during the last 3 nonmandatory years.

¹⁴An HMIS database is a local information technology system used to collect client-level data and data on the provision of housing and services to homeless individuals and families and persons at risk of homelessness. Each CoC is required by HUD to select HMIS software that complies with HUD’s data collection, management, and reporting standards.

¹⁵HUD has used its annual CoC funding process to incentivize annual sheltered and unsheltered counts. A majority of the CoCs conducted sheltered and unsheltered counts every year from 2013 through 2018 (specifically, 79 percent, 86 percent and 87 percent conducted sheltered and unsheltered counts in 2014, 2016 and 2018, respectively, which were off years).

CoC Efforts to Measure Homelessness Could Benefit from Strengthened HUD Oversight and Guidance

Point-in-Time Count Data Have Limitations for Measuring Homelessness

The data collected through the PIT count have limitations for the purpose of measuring homelessness. Researchers and CoC representatives noted that collecting data on the homeless population—particularly persons living in unsheltered locations—is inherently challenging. Several of these stakeholders told us that people experiencing unsheltered homelessness tend to take cover or hide in areas not visible to enumerators and may therefore be excluded from the unsheltered PIT count.¹⁶ Specifically, nine of the 12 researchers we interviewed said that finding people experiencing unsheltered homelessness is difficult given the hidden nature of this population. For example, *HUD's Point-in-Time Count Methodology Guide* states that it may not be safe to allow enumerators to enter abandoned buildings to look for people experiencing homelessness.¹⁷ Several researchers we interviewed also told us that people experiencing homelessness may not always exhibit visible behaviors—such as sleeping outside—that would identify them as potentially homeless. As a result, enumerators may struggle to determine whom they should count as homeless or interview.

In addition, the goals of collecting accurate PIT count data and serving the interests of people experiencing homelessness may not always be aligned. For example, *HUD's Point-in-Time Count Methodology Guide* notes that many CoCs instruct enumerators not to wake individuals who are sleeping out of respect. The guide also states CoCs may advise enumerators not to enter tents where homeless people may be sleeping. However, without interviews, enumerators have no way to determine, for instance, whether these individuals are chronically homeless or veterans. Further, while enumerators may estimate how many people are inside

¹⁶PIT count enumerators are those who count people experiencing homelessness on the night of the count. They are recruited and trained by CoC staff to assist with the PIT count. They may be volunteers or associated with the CoC.

¹⁷Department of Housing and Urban Development, *Point-in-Time Count Methodology Guide* (Washington, D.C.: 2014).

tents or use a multiplier to extrapolate the number of people likely to be inside, these approaches may produce less accurate data than a direct count of persons residing in tents would generate.

As a result of these challenges, the PIT count—particularly the unsheltered PIT count—likely underestimates the number of people experiencing homelessness at the time of the count.¹⁸ Seven of the 12 researchers we interviewed said they believed the sheltered PIT count underestimates the true size of the sheltered homeless population, and 10 researchers said they believed the unsheltered PIT count underestimates the true size of the unsheltered homeless population.¹⁹ None of the PIT focus group participants or researchers we spoke with thought the PIT count overestimates the true number of persons experiencing homelessness. Focus group participants and researchers also told us that the PIT count may be particularly likely to undercount some groups, such as homeless youth, families, and immigrants.²⁰

Our analysis also identified large year-over-year differences in CoCs' reported PIT counts, especially among suburban and rural CoCs. As figure 1 shows, suburban and rural CoCs appear to be more likely than urban CoCs to have an increase or decrease in their unsheltered PIT

¹⁸Because CoCs conduct the PIT count on a single night during the last 10 days of January, the PIT count naturally excludes persons experiencing homelessness who are not homeless at the time of the PIT count but are homeless at another point during the count year. As a result, our discussion of underestimation is limited to underestimation of homelessness at the time of the PIT count.

¹⁹These researchers cited several reasons why they believed the sheltered PIT count underestimates the size of the sheltered homeless population, including that it may exclude homeless individuals receiving shelter from homeless service providers that do not receive federal funding and therefore are not required to enter information into an HMIS database. While the extent to which the PIT count underestimates homelessness is unknown, the degree of underestimation researchers attributed to the sheltered PIT count was generally lower than the degree of underestimation they attributed to the unsheltered PIT count. One researcher said the unsheltered PIT count accurately estimates the number of people experiencing unsheltered homelessness at the time of the count, and one researcher was not sure. Moreover, four researchers said they believed the sheltered PIT count accurately estimates the number of people experiencing sheltered homelessness at the time of the count, and one was not sure.

²⁰To obtain information about how the PIT count, HMIS, and Housing Inventory Count are implemented in localities, we conducted four focus groups with a nongeneralizable, stratified random sample of 34 CoC officials who are responsible for collecting data on homelessness within their jurisdictions and reporting these data to the federal government. Two of these focus groups were focused on the PIT count and the Housing Inventory Count, and two were focused on HMIS.

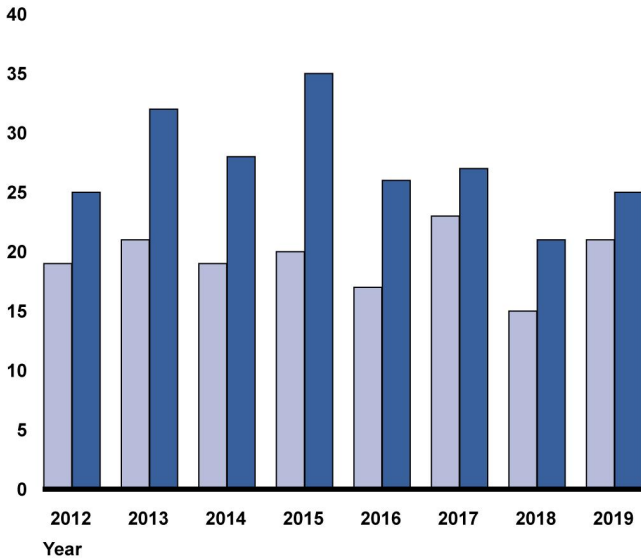
count exceeding 50 percent from the prior year.²¹ A 50 percent increase or decrease in a CoC's homeless population is possible but unexpected and raises concerns that the change does not reflect a true change in the size of the CoC's homeless population. Moreover, participants in our two focus groups on the PIT count and the Housing Inventory Count told us that a CoC's PIT count can change sharply from one year to the next due to events other than changes in the size of the homeless population—for example, a snow storm on the day of the count or a change in the number of enumerators. HUD officials told us that large CoCs in urban areas may have more capacity to execute the PIT count than smaller, more rural CoCs, which could play a role in the seemingly higher prevalence of large year-over-year changes in unsheltered PIT counts among suburban and rural CoCs.

²¹Because HUD does not require CoCs to report the measures of error associated with PIT count estimates obtained through sampling, we cannot determine whether the seemingly higher prevalence of large year-over-year differences among suburban and rural CoCs is statistically significant.

Figure 1: Percentage of Continuums of Care (CoC) with Year-over-Year Differences in Unsheltered and Sheltered Point-in-Time (PIT) Count Results Exceeding 50 Percent, 2012–2019

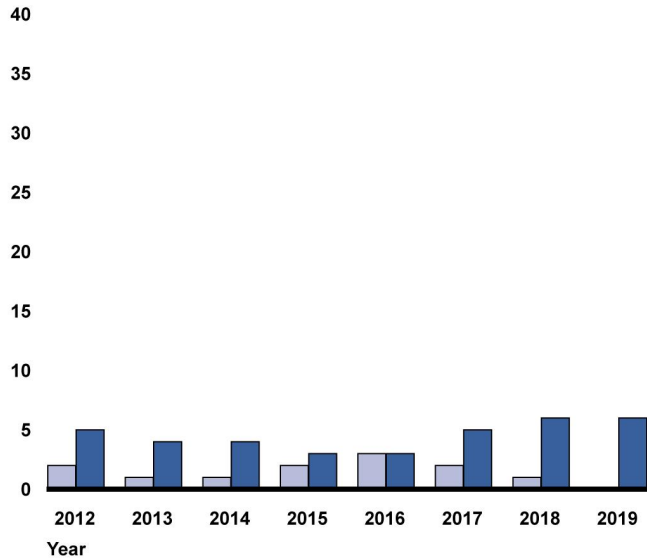
Unsheltered

Percent of CoCs with changes greater than ±50 percent



Sheltered

Percent of CoCs with changes greater than ±50 percent



Urban CoCs
Suburban and rural CoCs

Source: GAO analysis of Point-in-Time count data from the Department of Housing and Urban Development. | GAO-20-433

Data table for Figure 1: Percentage of Continuums of Care (CoC) with Year-over-Year Differences in Unsheltered and Sheltered Point-in-Time (PIT) Count Results Exceeding 50 Percent, 2012–2019

Year	Urban CoCs	Suburban and Rural CoCs
	Share of Unsheltered Changes Over 50%	Share of Unsheltered Changes Over 50%
2012	19%	25%
2013	21%	32%
2014	19%	28%
2015	20%	35%
2016	17%	26%
2017	23%	27%
2018	15%	21%
2019	21%	25%

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Year	Urban CoCs	Suburban and Rural CoCs
	Share of sheltered Changes Over 50%	Share of sheltered Changes Over 50%
2012	2%	5%
2013	1%	4%
2014	1%	4%
2015	2%	3%
2016	3%	3%
2017	2%	5%
2018	1%	6%
2019	0%	6%

Note: This figure shows the percentage of CoCs in each category with an increase or decrease in their PIT count of over 50 percent from the prior year. However, because HUD does not require CoCs to report the measures of error associated with PIT count estimates obtained through sampling, we cannot determine whether differences between suburban and rural CoCs and urban CoCs in the prevalence of large year-over-year changes are significant. We designated as “urban CoCs” those CoCs that the Department of Housing and Urban Development (HUD) categorized as “major cities” or “other largely urban” in 2019. We designated as “suburban and rural CoCs” those CoCs that HUD categorized as “largely suburban” or “largely rural” in 2019. In 2019, HUD classified approximately 12 percent of CoCs as major cities, 15 percent as other largely urban CoCs, 43 percent as largely suburban CoCs, and 29 percent as largely rural CoCs. Although CoCs’ geography types may have fluctuated from 2012 through 2019, we were only able to obtain CoC classifications for 2018 and 2019. However, among CoCs that existed in both 2018 and 2019, only two CoCs’ classifications changed during this period. Data presented are adjusted for mergers among CoCs from 2012 through 2019.

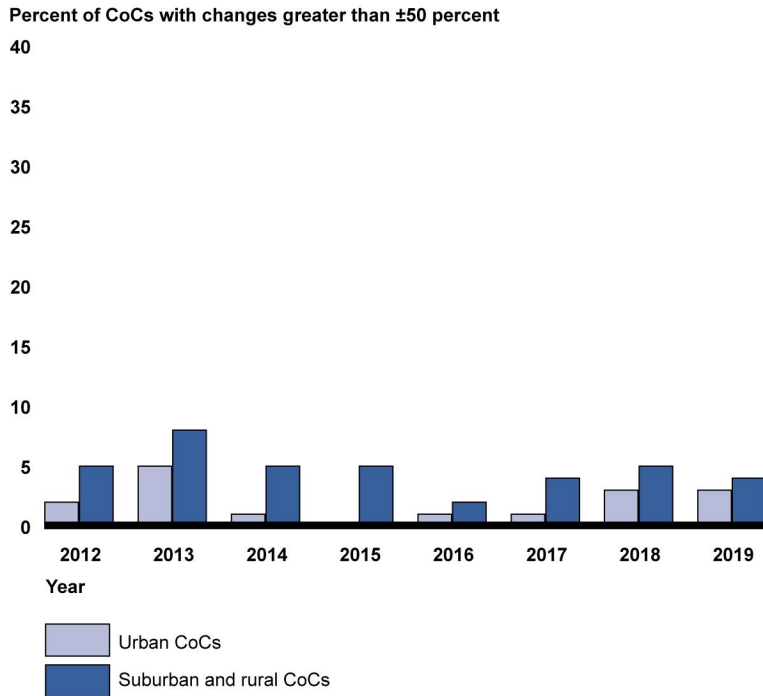
Our analysis also found that the unsheltered PIT count had a larger share of year-over-year differences above 50 percent than the sheltered PIT count. As figure 1 shows, few CoCs experienced large year-over-year differences in their sheltered PIT counts from 2012 through 2019, but a significant portion of CoCs’ unsheltered PIT counts varied considerably during this period. In particular, the median magnitude of change in CoCs’ sheltered PIT counts was 10 percent per year from 2012 through 2019, compared to 26 percent per year for their unsheltered PIT counts.²²

CoCs’ total PIT counts, composed of the sheltered and unsheltered counts, experienced relatively few large year-over-year differences from 2012 through 2019. Specifically, as figure 2 shows, among CoCs of both geographic types, fewer than 10 percent of CoCs reported changes in their total PIT counts exceeding 50 percent from the prior year. Because the sheltered PIT count represents a larger portion of the total PIT count than does the unsheltered PIT count, the volatility in CoCs’ unsheltered PIT counts appears to have had a relatively modest effect on the overall count. For example, in 2019, the unsheltered PIT count represented 37

²²These percentage changes are absolute values. For example, we treated a 10 percent increase and a 10 percent decrease equivalently for the purpose of this calculation.

percent of the total, while the sheltered PIT count represented 63 percent of the total.

Figure 2: Percentage of Continuums of Care (CoC) with Year-over-Year Differences in Total Point-in-Time (PIT) Count Results Exceeding 50 Percent, 2012–2019



Source: GAO analysis of Point-in-Time count data from the Department of Housing and Urban Development. | GAO-20-433

Data table for Figure 2: Percentage of Continuums of Care (CoC) with Year-over-Year Differences in Total Point-in-Time (PIT) Count Results Exceeding 50 Percent, 2012–2019

Year	Urban CoCs	Suburban and Rural CoCs
2012	2%	5%
2013	5%	8%
2014	1%	5%
2015	0%	5%
2016	1%	2%
2017	1%	4%
2018	3%	5%
2019	3%	4%

Note: This figure shows the percentage of CoCs in each category with an increase or decrease in their PIT count of over 50 percent from the prior year. However, because the Department of Housing and Urban Development (HUD) does not require CoCs to report the measures of error associated

with PIT count estimates obtained through sampling, we cannot determine whether differences between suburban and rural CoCs and urban CoCs in the prevalence of large year-over-year changes are significant. We designated as “urban CoCs” those CoCs that HUD categorized as “major cities” or “other largely urban” in 2019. We designated as “suburban and rural CoCs” those CoCs that HUD categorized as “largely suburban” or “largely rural” in 2019. In 2019, HUD classified approximately 12 percent of CoCs as major cities, 15 percent as other largely urban CoCs, 43 percent as largely suburban CoCs and 29 percent as largely rural CoCs. Although CoCs’ geography types may have fluctuated from 2012 through 2019, we were only able to obtain CoC classifications for 2018 and 2019. However, among CoCs that existed in both 2018 and 2019, only two CoCs’ classifications changed during this period. Data presented are adjusted for mergers among CoCs from 2012 through 2019.

Better HUD Monitoring and Guidance Could Enhance Homelessness Data Collection

HUD’s homelessness data are critical sources of information on the number and characteristics of people who are homeless in the United States. For example, PIT count data help Congress to assess the efficacy of federal homelessness programs, HUD to allocate funding to CoCs, and HUD and CoCs to plan federal and local responses to homelessness. HUD has taken steps to improve the accuracy and reliability of its data on homelessness. However, we found there were opportunities for improvement in three areas: its data on CoCs’ PIT count methodologies, how it accounts for sampling error and bias, and the assistance it provides to CoCs on data collection. Improvements in these areas would support the federal and local efforts that rely on HUD’s homelessness data.

Methodological Variation

One explanation for the limitations of PIT count data relates to variation in the methodologies CoCs use to execute their PIT counts. Specifically, methodological variation makes it challenging to compare or aggregate across different CoCs’ PIT counts. HUD allows CoCs to choose among several different methodologies for conducting their PIT counts. For example, a CoC can use a “known locations” sample, in which enumerators canvass areas where people experiencing homelessness are known to be located, or a random sample, in which enumerators canvass areas selected at random. For both options, findings from the sampled areas are extrapolated to the full CoC. Alternatively, a CoC can perform a complete census in which enumerators canvass the CoC’s entire jurisdiction and attempt to locate and count all unsheltered homeless individuals in the area on the night of the count. Many CoCs use a combination of these and other methods to execute their PIT counts. It would be difficult for all CoCs to implement the same methodology because CoCs vary greatly in terms of size, geography,

population density, and other factors. For example, the entire state of South Dakota, which is over 77,000 square miles, and the city of San Francisco, which is just 47 square miles, both represent single CoCs.

CoCs can also change methodologies from year to year. Although CoCs may change their PIT count methodologies in an effort to better capture homelessness within their jurisdictions, these changes nonetheless affect the comparability of data over time, both across CoCs and within a given CoC. As seen in table 2, some CoCs changed their unsheltered PIT count methodologies from 2018 to 2019 (the 2 most recent years for which this information was available from HUD).

Table 2: Changes Continuums of Care (CoC) Made to Unsheltered Point-in-Time (PIT) Count Methodologies from 2018 to 2019

Methodological change	Percentage of CoCs that made this change
Increased or decreased the use of Homeless Management Information System databases to derive unsheltered counts	17
Increased or decreased the use of service-based surveys to derive unsheltered counts ^a	22
Added or removed a known locations sample to their unsheltered methodology ^b	23
Added or removed a census to their unsheltered methodology	25
Added or removed a random sample to their unsheltered methodology	4

Source: GAO analysis of PIT count methodology data from the Department of Housing and Urban Development. | GAO-20-433

Notes: To capture changes CoCs made to their PIT count methodologies, rather than changes CoCs made to their participation in optional PIT counts or changes in the population of CoCs, we examined a stable population of CoCs. In particular, the percentages given in this table are for the 328 CoCs that conducted sheltered and unsheltered PIT counts each year from 2016 through 2019. Within this group of CoCs, we examined changes CoCs made to their methodologies from 2018 to 2019, the 2 most recent years for which data are available. Some CoCs changed multiple aspects of their PIT count methodologies from 2018 to 2019.

^aService-based counts are conducted at locations frequented by people who are homeless, including soup kitchens, day shelters, libraries, and other community locations. Enumerators interview all people at these locations to identify who was unsheltered on the night of the count and determine their characteristics.

^bFor known locations samples, enumerators canvass areas where people experiencing homelessness are known to be located, and the results are extrapolated to the full CoC.

In addition, changes in the numbers of enumerators can affect the accuracy of a CoC’s PIT count. HUD does not systematically collect data on the number of enumerators CoCs recruit to assist with their PIT counts. However, CoC participants in each of our two focus groups on the PIT count and the Housing Inventory Count said that the number of enumerators participating in their counts sometimes changed significantly from one year to the next. For example, one CoC representative told us that a blizzard on the night of the PIT count caused an unexpected drop in enumerator turnout, which affected the CoC’s ability to cover its entire area in a single night.

According to HUD data, many CoCs reported changing various aspects of their sheltered PIT count methodologies from 2018 to 2019 (see table 3).

Table 3: Changes Continuums of Care (CoC) Made to Sheltered Point-in-Time (PIT) Count Methodologies from 2018 to 2019

Methodological change	Percentage of CoCs that made this change
Increased or decreased the use of Homeless Management Information System databases (HMIS) to derive sheltered counts	32
Increased or decreased the use of provider surveys to derive sheltered counts	26
Increased or decreased the use of client surveys to derive sheltered counts	23
Increased or decreased the use of observation to derive sheltered counts	2
Increased or decreased the use of other methods to derive sheltered counts	5

Source: GAO analysis of PIT count methodology data from the Department of Housing and Urban Development. | GAO-20-433

Notes: To capture changes CoCs made to their PIT count methodologies, rather than changes CoCs made to their participation in optional PIT counts or changes in the population of CoCs, we examined a stable population of CoCs. In particular, the percentages given in this table are for the 328 CoCs that conducted sheltered and unsheltered PIT counts each year from 2016 through 2019. Within this group of CoCs, we examined changes CoCs made to their methodologies from 2018 to 2019, the 2 most recent years for which data are available. Some CoCs changed multiple aspects of their PIT count methodologies from 2018 to 2019. CoCs report to the Department of Housing and Urban Development the percentage of their sheltered PIT counts derived from HMIS data, provider surveys, client surveys, observation, and other methods. For the purpose of this analysis, we defined a change from one year to the next to be an increase or decrease of more than 10 percentage points of a CoC's sheltered PIT count that the CoC derived from one of these sources.

HUD's Office of Special Needs Assistance Programs collects data on the methodologies CoCs employ for their PIT counts. CoCs submit their PIT count results to HUD via an online tool called the Homelessness Data Exchange, and HUD aggregates the results to form a PIT count methodology dataset. As part of the submission process, CoCs must respond to questions about their methodologies, including both closed-ended questions, such as multiple-choice and fill-in-the-blank questions, and open-ended questions seeking a narrative response. This information helps HUD ensure that CoCs employ methods consistent with HUD's standards.

Our review found that some of the variables in HUD's methodology dataset were incomplete in some years.²³ For example:

- In 2014, 2015, 2018, and 2019, there were numerous missing values related to deduplication of sheltered counts.²⁴ Less than one-third of

²³Though our analysis found a number of incomplete variables in HUD's methodology dataset, the PIT count methodology variables summarized in tables 2 and 3 did not contain any missing values in 2018 or 2019.

²⁴Deduplication is the process by which CoCs ensure people experiencing homelessness do not have duplicate records in their databases.

CoCs fully responded to a question about the techniques used to deduplicate the counts in those years. In 2015 and 2019, there were missing values related to the deduplication of unsheltered counts for more than two-thirds of CoCs.²⁵ In 2013, 2016, and 2017, almost all CoCs responded fully to HUD's questions about the techniques used to ensure duplicated records were addressed, but some CoCs (less than 4 percent in 2017) left fields blank.

- In 2017, 2018, and 2019, some CoCs did not provide narrative descriptions of the causes of changes to their sheltered counts compared to the previous year (15, 19, and 17 percent, respectively).²⁶ HUD does not require CoCs to complete narrative fields. CoCs that choose to provide narrative responses are not required to provide evidence to support their responses. As a result, HUD cannot be assured this information is accurate.
- In 2015, 56 CoCs (or 14 percent) did not respond when asked if geographic areas or homeless persons within the CoC had been sampled for the unsheltered count. In comparison, for the 2017 and 2019 unsheltered counts, 98 percent of CoCs responded to these questions.
- When CoCs could select "other" as a response, some CoCs did not add required narrative to specify the response. For example, in 2019 34 CoCs selected "other" when asked what factors explained changes to their sheltered PIT count from the preceding year but did not specify their response as required.

Complete information about CoCs' methodologies would help HUD better understand PIT count trends and results.

HUD officials also told us that they do not conduct quality assurance checks to assess the accuracy of the information CoCs provide about their methodologies, although at times they may call CoC staff to obtain clarification about unusual responses. However, HUD officials said that when they obtain accurate information from these follow-up efforts, they do not update their methodology dataset to reflect the correct information. Moreover, HUD officials told us they are unsure whether some CoCs that report using census methodologies for unsheltered PIT counts may

²⁵CoCs are not required to conduct unsheltered PIT counts in even-numbered years.

²⁶The number of CoCs that did not provide this information in 2017, 2018, and 2019 was 63, 77, and 68, respectively.

actually be using probability sampling techniques. Specifically, officials said these CoCs may be randomly selecting areas to canvass and applying a sampling technique to areas not canvassed, raising a concern that HUD's methodology dataset may not accurately reflect the methodologies CoCs implement.

Because of these limitations, HUD cannot consistently ensure that CoCs' PIT count methodologies comply with HUD standards. Moreover, given the variation in PIT count methodologies across and within CoCs, HUD's methodology dataset provides important context when comparing different CoCs' PIT count results. HUD's methodology dataset can also help HUD identify CoCs with capacity challenges and provide them with assistance. However, the lack of complete information in the dataset limits HUD's ability to identify CoCs with relatively less capacity to produce a quality estimate of homelessness.

According to HUD's *Point-in-Time Count Methodology Guide*, the PIT count should provide valid and reliable results.²⁷ Additionally, federal internal control standards state that management should use quality information to achieve the entity's objectives.²⁸ In particular, the standards call for agencies to ensure that external sources provide data that are reasonably free from error and bias and represent what they purport to represent. Quality assurance checks on its methodology dataset would provide reasonable assurance that HUD's standards for PIT count data collection are being met.

Sampling Error and Bias

Error and bias associated with probability sampling techniques may also partially explain the limitations associated with CoCs' PIT counts, particularly their unsheltered PIT counts.²⁹ As discussed earlier, HUD's PIT count standards, developed by the Office of Special Needs

²⁷Department of Housing and Urban Development, *Point-in-Time Count Methodology Guide*.

²⁸[GAO-14-704G](#).

²⁹Previous studies have also explored the effect of sampling variability on PIT count estimates. For example, see Chris Glynn, Thomes H. Byrne, and Dennis P. Culhane, "Quantifying Uncertainty in HUD Estimates of Homelessness," (2018), accessed February 28, 2020, http://files.zillowstatic.com/research/public/StaticFiles/Homelessness/Quantifying_Uncertainty_HUD.pdf.

Assistance Programs, allow CoCs to either conduct a full census or use a probability sample and extrapolation to estimate the number of persons experiencing homelessness at the time of the count. CoCs use sampling techniques more commonly for their unsheltered PIT counts than for their sheltered PIT counts. Specifically, in 2019, at least 87 percent of CoCs used a sampling technique for their unsheltered PIT counts, and 17 percent of CoCs used sampling for their sheltered PIT counts.³⁰ A CoC that uses probability sampling can use a measure of error to estimate sampling error—the extent to which its PIT count may deviate from the true size of its homeless population on the night of the count.³¹ If the measure of error is large, apparent changes in the CoC’s PIT count from year to year may be the result of sampling error rather than a true increase or decrease in the CoC’s homeless population. However, HUD does not require CoCs to report the measures of error associated with PIT count estimates obtained through sampling.

Sampling error. According to federal standards for statistical surveys, the sampling errors associated with population estimates should be quantifiable and should be provided alongside the population estimates to which they correspond.³² HUD officials told us they have considered requiring CoCs to report the measures of error associated with their PIT counts but have stopped short of doing so because they believe sampling error is a difficult concept to convey to the public, and some CoCs may lack the technical expertise to develop measures of error. Resource constraints may also affect some CoCs’ ability to develop measures of error. For example, some CoC focus group participants told us limited resources affect their ability to produce accurate data on homelessness.

³⁰In 2019, CoCs based their sheltered PIT counts on information from HMIS databases, provider surveys, client surveys, observation, and other techniques. According to the methodology descriptions in HUD’s *Point-in-Time Count Methodology Guide*, the only one of these approaches that involves probability sampling is client surveys, and 19 percent of CoCs used client surveys for their sheltered PIT count in 2019. Alternatively, in 2019, CoCs based their unsheltered PIT counts on information from HMIS databases, known locations samples, random samples, service-based counts, and complete censuses. Of these approaches, both known locations samples and random samples involve probability sampling. In 2019, 87 percent of CoCs used a known locations sample for their unsheltered PIT count, and 7 percent of CoCs used a random sample for their unsheltered PIT count. Some CoCs may have used a combination of these probability sampling techniques.

³¹“Measures of error” include variance, standard errors, margins of error, confidence intervals, and coefficients of variation, among others.

³²Office of Management and Budget, *Standards and Guidelines for Statistical Surveys*.

HUD officials also said that sampling variability is not the only source of error in PIT count estimates. However, HUD does not currently report estimates of the extent of any possible sources of error in PIT count estimates. When CoCs use sampling techniques to generate their PIT counts without providing the accompanying measures of error, this may create a perception that the count is more precise than it actually is. Further, without measures of error, HUD and other users of PIT count data cannot assess whether year-over-year changes in a CoCs' PIT counts are meaningful.

Sampling bias. Federal standards for statistical surveys also state that agencies should estimate the potential bias associated with counts used to derive estimates.³³ Sampling bias occurs when some homeless people have a lower probability of being included in a CoC's PIT count sample than others. As discussed previously, any method of counting the unsheltered homeless population has the potential to miss some homeless people due to, among other things, the hidden nature of the population. As a result, PIT count estimates are prone to some degree of bias.³⁴ In particular, these challenges may result in underestimation of people experiencing homelessness, particularly for subpopulations that are difficult to identify and count.³⁵ However, HUD does not require CoCs to estimate the potential level of bias associated with PIT count estimates obtained through sampling. Without accounting for potential bias, HUD

³³An example of a method CoCs could employ to estimate the level of bias associated with PIT count estimates involves planting "decoys"—volunteers pretending to be homeless—during the unsheltered PIT count and seeing how many of these decoys enumerators miss. Some CoCs have already implemented similar approaches, though HUD does not require it. However, one technical assistance provider we interviewed expressed concerns about the appropriateness of volunteers posing as people experiencing homelessness.

³⁴The potential for bias also applies to census methodologies. HUD's *Point-in-Time Count Methodology Guide* states that census counts provide the most complete and accurate information available. However, the challenges associated with finding and counting people in unsheltered locations also make it difficult for CoCs employing census methods to perform exhaustive counts. Nonetheless, bias may be particularly problematic with respect to probability samples. Specifically, if an estimate obtained from a sample is biased, that bias may be magnified when the sample estimate is extrapolated across unsampled areas. Department of Housing and Urban Development, *Point-in-Time Count Methodology Guide*.

³⁵Although our analysis found that the PIT count likely underestimates homelessness overall, and unsheltered homelessness in particular, subpopulations that are easier for enumerators to identify and count may be overrepresented in the PIT count due to sampling bias.

and users of PIT count data cannot assess the degree to which the PIT count data have excluded individuals that should have been counted.

HUD also does not provide CoCs with detailed instructions on using probability sampling techniques. CoCs may lack staff with statistical experience and may need instructions in order to use these techniques correctly. Furthermore, a probability sample requires first having a reliable basis for the size of the sampled population, which HUD does not provide instructions for obtaining. HUD officials told us they believe CoCs that use probability sampling cannot confidently say they measured a random sample of the population, yet a random sample is one of the methodology options HUD provides to CoCs (a known locations sample is another option). CoCs' frequent use of probability sampling techniques highlights the importance of appropriate instructions. HUD guidance states that CoCs must base their PIT counts on actual counts or statistically reliable estimation methods.³⁶ Detailed instructions on using probability sampling techniques to produce PIT count estimates would provide HUD greater assurance that CoCs produce valid results using such methods.

HUD Assistance

HUD and its technical assistance providers offer assistance to CoCs through quarterly PIT count office hours, one-on-one conversations with CoC representatives, and email announcements, among other means. However, during our three site visits and in each of the four focus groups we conducted with a total of 34 CoC representatives, participants identified aspects of HUD's assistance on data collection and reporting that did not fully meet their needs. In particular, both HMIS focus group participants and participants from our focus groups on the PIT count and the Housing Inventory Count said they would benefit from additional technical support and training from HUD, as well as additional resources for capacity building. They also identified challenges with several aspects of HUD's assistance:

- **Clarity of definitions.** In structured interviews and focus groups, CoC representatives told us they were confused about how to meet certain data standards. Participants from our HMIS focus groups as well as our focus groups on the PIT count and Housing Inventory Count said the definitions of some categories HUD uses are confusing or unclear.

³⁶Department of Housing and Urban Development, *2019 Housing Inventory Count and Point-in-Time Count of Homeless Persons: Data Submission Guidance* (Washington, D.C.: 2019).

For example, they said they could benefit from additional clarity from HUD on how to apply the standards to classify and define certain people as either chronically homeless or homeless veterans. Furthermore, HMIS focus group participants said knowing whether to classify someone as a homeless veteran can be confusing. They noted that there is a difference between a self-reported veteran and one that qualifies for VA assistance, and eligibility requirements vary among homeless assistance programs for veterans. Some focus group participants told us they were uncertain when to classify an individual as chronically homeless.³⁷ HUD provides a flowchart CoCs can use to determine an individual's status, along with webinars and online responses to frequently asked questions on determining chronicity. However, our review found that the flowchart does not define key terms used to navigate it, such as "qualifying disability," and there are 12 possible paths through the flowchart, potentially making it complex for CoCs to use. Participants in one of our HMIS focus groups also stated that they would like clarity on how they should ask homeless clients about their history to assess whether they meet HUD's definition of chronic homelessness.

- **Ask-A-Question tool.** CoC staff can use HUD's online Ask-A-Question tool to obtain clarification on HUD standards and requirements, including its three data sources on homelessness. HUD officials told us that the targeted response time to Ask-A-Question submissions is 7 to 10 days, but CoC participants in one of our HMIS focus groups told us they need responses sooner. Participants in this focus group also told us HUD's Ask-A-Question responses sometimes referred them back to written HUD policy documents that did not address their questions.
- **Volume of guidance.** Some CoC focus group participants told us that keeping pace with the volume of HUD guidance on data collection has been difficult. HUD officials told us they communicate guidance through updates to the HMIS data standards; training for CoC staff;

³⁷To meet HUD's CoC program definition of chronic homelessness, an individual must meet disability, living situation, and timing requirements. Individuals are considered chronically homeless if they have a serious disabling condition and live in a place not meant for human habitation; a safe haven; an emergency shelter; or less than 90 days in institutional care facility after living in a place not meant for human habitation, safe haven, or emergency shelter. Further, individuals generally must have been living under these circumstances continuously for at least 12 months or on at least four separate occasions in the last 3 years, where the combined periods of time total at least 12 months. 24 C.F.R. § 578.3. HUD's final rule with the definition of chronic homelessness went into effect in January 2016.

tools, webinars, and guidance documents; presentations by HUD staff during conferences; facilitated discussions, such as conference calls and Community of Practice meetings with CoC representatives; and email announcements, among other methods. In 2014, 2016, 2017, and 2020, HUD released updated HMIS data standards, which include all requirements for the programming and use of HMIS databases. HMIS focus group participants reported that keeping up with increasing data collection requirements and changing data standards has been difficult.

As noted earlier, according to HUD's *Point-in-Time Count Methodology Guide*, the PIT count should provide valid and reliable results. In addition, federal internal control standards state that management should externally communicate the necessary quality information to achieve the entity's objectives.³⁸ HUD's Office of Special Needs Assistance Programs published a data strategy in May 2017 to present its vision for optimal data systems and data usage, but the strategy does not include an assessment of the assistance that HUD provides to CoCs regarding data collection. By taking steps to better ensure that its data collection assistance meets the needs of CoCs, HUD could improve CoCs' ability to apply its standards consistently.

HUD's Other Homelessness Data Are Relatively Reliable, and HUD Is Taking Steps toward Improvement

In addition to the PIT count, HUD's two other key sources of data on homelessness—HMIS databases and the Housing Inventory Count—have some limitations but provide relatively reliable information on homelessness. HMIS databases and the Housing Inventory Count provide information on sheltered homelessness, whereas the PIT count provides information on both sheltered and unsheltered homelessness. HUD officials told us they have ongoing efforts to improve the accuracy and reliability of these two data sources.

HMIS Databases

The majority of the 11 researchers we interviewed who commented on HMIS data said HMIS databases are a reliable source of information on changes in the homeless population. Our analysis also identified several strengths of HMIS data. In particular, seven researchers said HMIS data

³⁸[GAO-14-704G](#).

are reliable or very reliable for understanding changes in homelessness at the national level, and eight researchers said HMIS data are reliable or very reliable for understanding changes in homelessness at the local level. Our analysis found that the strengths of HMIS data include the following:

- **Continuously collected data.** While the PIT count and the Housing Inventory Count attempt to provide a snapshot of homelessness on a single night per year, CoCs can continually update their HMIS databases throughout the year. As a result, HMIS databases provide greater insight into trends over time. Five researchers we interviewed cited the ability to collect data continuously as a particular strength of HMIS data.
- **Individual-level data.** HMIS data are collected on a more granular level than PIT count or Housing Inventory Count data. In particular, HMIS databases collect information on individual persons experiencing homelessness, which allows CoCs to analyze HMIS data in a number of ways. For example, CoCs can generate reports for certain projects or subpopulations from their HMIS databases. HMIS data can also be aggregated to produce CoC-level reports analogous to the PIT count and Housing Inventory Count.
- **Comprehensive scope of sheltered data.** HMIS databases are a source of relatively comprehensive information on sheltered homelessness because they mainly collect data on homeless people who are receiving services from a homeless service provider. As discussed earlier, the sheltered population is easier to locate and count compared to the unsheltered population.

Although our analysis found that HMIS databases include reasonably accurate information about the homeless population, particularly those living in shelters, data from these systems also have some limitations. These limitations do not significantly affect the overall reliability of the data:

- **Limited data from nonfederal providers.** Homeless service providers that do not receive federal funding are not required to input data in their CoC's HMIS, which results in gaps in data coverage. However, CoCs may recruit such providers to participate in their HMIS databases voluntarily to increase the comprehensiveness of the CoC's HMIS data.

- **Timeliness of updates.** Some CoC focus group participants told us that the information homeless service providers enter into their CoCs' HMIS databases may not always be current. For example, they said that some providers retroactively update clients' HMIS records well after changes in their status have occurred, which results in HMIS data that are out-of-date until providers update their records. One HMIS focus group participant said that at one of their CoC's large shelters, volunteers collect intake data on paper, and these data are entered into HMIS at a later date. This participant also noted that the volunteers are not trained in data collection, which affects the quality of the data collected.
- **Scope of unsheltered data.** HMIS databases primarily collect data on persons experiencing sheltered homelessness. CoCs vary in whether and the degree to which they add unsheltered individuals to their HMIS databases, making these figures hard to compare across CoCs and potentially across years within a CoC.
- **Potential duplication.** Homeless clients who receive services in multiple CoCs may have records in multiple CoCs' HMIS databases. According to our technical assistance provider discussion group, this may result in potential duplication when data are aggregated at the national level.

Efforts are also underway to improve HMIS data. For example, HUD officials told us that implementation of coordinated entry has improved HMIS data quality.³⁹ Coordinated entry encourages homeless service providers to use their CoC's HMIS database to assess clients' needs and refer them to appropriate services. HUD also recently awarded \$5 million in grants to help CoCs fund improvements to their HMIS databases. Additionally, HUD recently changed how it receives summary reports from CoCs' HMIS databases for use in the Annual Homeless Assessment Report for Congress. Specifically, in 2018, HUD began collecting HMIS summary reports through a new method called the Longitudinal Systems Analysis.⁴⁰ According to HUD officials, this new method will simplify the data collection and reporting process, potentially leading to better quality data. HUD officials also told us that the number of CoCs providing usable

³⁹Coordinated entry is a process whereby homeless service providers work together to deliver assistance through a coordinated referral and housing placement process.

⁴⁰The Annual Homeless Assessment Report to Congress is a HUD report that provides nationwide estimates of homelessness, including information about the demographic characteristics of homeless persons, service use patterns, and the capacity to house homeless persons.

HMIS summary reports to inform the Annual Homeless Assessment Report has increased over time. As a result, HUD is able to develop its report using HMIS summaries from all CoCs, rather than from a sample of CoCs with relatively better data, as HUD previously did. It is too early to determine whether CoC staff find the new method more efficient than HUD's prior HMIS reporting process.

Housing Inventory Count

We found that Housing Inventory Count data are reasonably reliable for understanding changes in the stock of housing and beds available to address homelessness. Three of the six researchers we interviewed who commented on Housing Inventory Count data described them as reliable or very reliable for understanding changes in the stock of housing available to address homelessness at the national or local level. Two of these researchers also noted that the quality of Housing Inventory Count data has improved over time, and our electronic testing of these data did not identify obvious errors.

Housing Inventory Count data also have some limitations, although these limitations do not significantly affect the overall reliability of the data. Specifically, four of the six researchers who commented on these data noted that they exclude some homeless service providers. Participants in one of our focus groups on the PIT count and the Housing Inventory Count agreed and told us that the Housing Inventory Count may be particularly prone to missing providers that do not receive federal funding. A few CoC focus group participants also said developing a bed count can be challenging because some beds in a CoC are for people who do not fit HUD's definition of homeless.

HUD has efforts underway designed to improve the quality of Housing Inventory Count data. For example, CoC participants in one of our focus groups on the PIT count and the Housing Inventory Count said that HUD has better specified how information collected in HMIS databases should be reported in CoCs' Housing Inventory Count submissions. As a result, HUD officials told us more CoCs are able to complete their Housing Inventory Counts by obtaining the information HUD requires them to report directly from their HMIS databases. HUD officials also told us that their efforts to help CoCs improve the quality of Housing Inventory Count data have resulted in more projects being included in the Housing Inventory Count.

Recent Changes in Homelessness Reflect a Mix of Economic and Social Factors

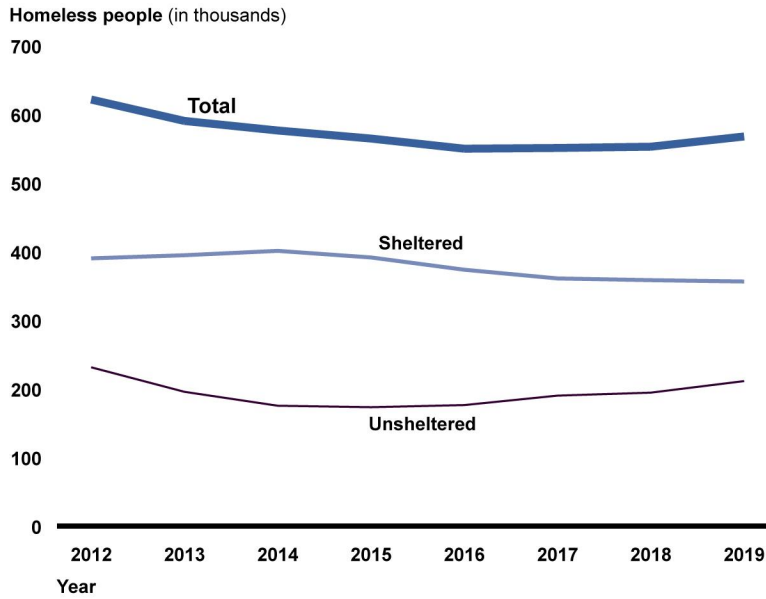
Estimated Homelessness Decreased from 2012 through 2016 but Increased Slightly From 2017 to 2019 Due to Increases in the Unsheltered Population

In 2019 the PIT count estimated that on a given night in the United States nearly 568,000 people were experiencing homelessness, representing about 0.2 percent of the resident U.S. population.⁴¹ This count is a decline from about 621,500 in 2012, but is a slight increase over the period's low of about 550,000 in 2016 (see fig. 3).⁴²

⁴¹Resident population was 328,239,523 people in 2019 based on U.S. Census Bureau estimates.

⁴²As previously stated, PIT count data have a number of limitations. Although PIT counts for individual CoCs may be subject to a high degree of variability between years, largely due to the unsheltered population, the overall PIT count may generally represent the trend of homelessness because the proportion of the unsheltered population is relatively small. To use PIT count data for our trend analysis, we limited our analysis to years 2012 through 2019 due to improvements in PIT count data, and we accounted for merged CoCs.

Figure 3: Total Homelessness, 2012–2019



Source: GAO analysis of Department of Housing and Urban Development data. | GAO-20-433

Data table for Figure 3: Total Homelessness, 2012–2019

Year	Total	Sheltered	Unsheltered
2012	621.553	390.155	231.398
2013	590.364	394.698	195.666
2014	576.45	401.051	175.399
2015	564.708	391.44	173.268
2016	549.928	373.571	176.357
2017	550.996	360.867	190.129
2018	552.83	358.363	194.467
2019	567.715	356.422	211.293

Note: U.S. Census Bureau estimates of the resident population of the United States grew by approximately 4.6 percent over the same period and did not decline in any given year.

Estimated unsheltered homelessness followed the same trend as estimated total homelessness, declining from 2012 through 2015 but increasing from 2016 through 2019 (see fig. 3).⁴³ The estimated total number of people experiencing unsheltered homelessness on a given night increased by more than the count of total sheltered homelessness

⁴³Due to a number of problems related to counting unsheltered persons, as discussed earlier, unsheltered homelessness is likely undercounted.

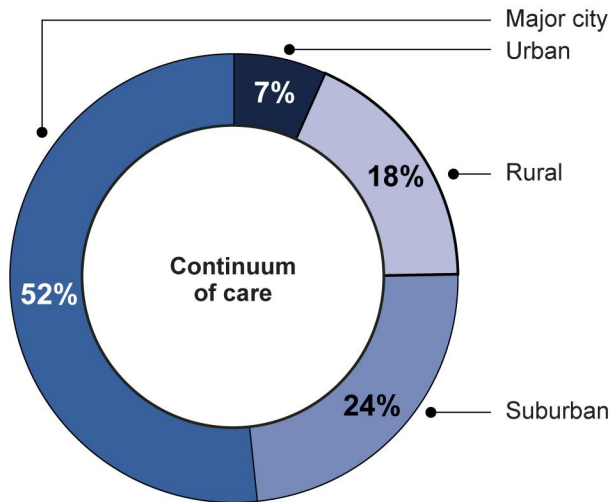
decreased from 2016 to 2019, causing a slight uptick in the overall PIT count. Unsheltered homelessness represented approximately 32 percent of counted homelessness in 2016 and approximately 37 percent in 2019. The sheltered homelessness count increased from 2012 through 2014 by about 3 percent, but declined by 11 percent from 2014 to 2018.

The PIT count attempts to count certain subpopulations, including homeless people in families and homeless individuals (those not experiencing homelessness as part of a family). From 2012 through 2019, the estimate of homeless people in families decreased every year by approximately 28 percent in total (from 239,397 to 171,670). While the total estimate of homeless individuals declined from 2012 through 2016, it increased from 2016 through 2019 by about 11 percent, which reflects the directional trend of the total count of the homeless population.

Major city CoCs were the only CoCs that experienced an overall increase in counted homeless people from 2012 through 2019.⁴⁴ Our analysis of PIT count data indicates that during this period, major city CoCs experienced approximately a 13 percent overall increase in estimated homelessness. Approximately 52 percent of all counted homeless people lived in a major city CoC in 2019 (see fig. 4). Urban (which does not include major city), suburban, and rural CoCs all experienced an overall decline in estimated homelessness from 2012 through 2019 of approximately 10, 26, and 26 percent, respectively. Despite an overall decline since 2012, urban CoCs experienced a slight increase in counted homeless people from 2017 to 2019. Rural CoCs also experienced a slight increase in counted homeless people from 2018 to 2019.

⁴⁴CoC classification as major city, largely urban, largely suburban, or largely rural is based on the 2019 HUD classification of those CoCs. HUD began classifying CoCs in 2018, and thus any CoC that no longer existed by 2018 is not included in these figures. An individual CoC may comprise areas with different degrees of urbanicity, and HUD classifies a CoC as major city, largely urban, largely suburban, or largely rural based on where the greatest percentage of its population lives. As a result, a person experiencing homelessness could live, for example, in a rural CoC but not necessarily live in a rural area.

Figure 4: Geographic Distribution of U.S. Homelessness by Continuum of Care Classification in 2019



Source: GAO analysis of Department of Housing and Urban Development data. | GAO-20-433

Data table for Figure 4: Geographic Distribution of U.S. Homelessness by Continuum of Care Classification in 2019

	Total Homeless(2019)	% of total
Major City	292882	0.515896
Urban	37774	0.066537
Suburban	134788	0.237422
Rural	102271	0.180145
Total	567715	1

Note: Percentages total more than 100 percent due to rounding.

From 2014 through 2019, major city CoCs also experienced consistent growth in the count of unsheltered homeless people. During the entire 2012 through 2019 period, the unsheltered homeless count increased by about 36 percent, or approximately 30,000 people, in major city CoCs. From 2018 to 2019 alone, the count of unsheltered homelessness increased by approximately 12 percent, or about 11,000 people, within major city CoCs. Although the total count of unsheltered homeless people declined in suburban and rural CoCs from 2012 through 2019, the unsheltered homeless count increased in all classifications of CoCs from 2018 to 2019.

Analysis of Available Data Suggests an Association between Rental Prices and Homelessness Rates, and Other Factors May Also Be Relevant

Homelessness cannot generally be attributed to a single factor but is often the result of the interaction of a multitude of factors. We developed an econometric model to examine the relationship between homelessness and a number of explanatory variables. Evidence from our econometric analysis shows a statistically significant relationship between changes in household median rents and changes in rates of homelessness counts even after accounting for a variety of factors.⁴⁵ Household median rent represents the rent across all unit sizes and types paid by individual renters or households rather than the cost of the unit. As such, the household median rent for a unit shared among multiple households is divided among those households. In addition, interviews with local officials and homeless service providers also suggest that the cost of housing is seen as an influential factor related to the number of people experiencing homelessness from 2012 through 2018.

Our model is based on all CoCs in the United States for which there are data for 2012 through 2018, and the model is designed to estimate the extent to which different factors are related to changes in the rates of homelessness within CoCs over time, but not to directly examine factors that are related to levels of homelessness across CoCs. We included several variables in our model such as median rent, wages, unemployment rate, and poverty, as well as other demographic and economic characteristics. The model is not meant to disentangle the specific cause of any changes in homelessness; rather, it is meant to establish whether there were any statistically significant relationships between changes in the rates of homelessness counts and any given

⁴⁵Household median rent refers to the American Community Survey's median gross rent, which includes estimates of paid utilities. The survey calculates the median based on the share of the rent paid by the households or individuals occupying the surveyed housing unit rather than the total rent for the entire unit.

factor.⁴⁶ Appendix II provides a detailed discussion of our analysis and its limitations.

As discussed earlier, PIT count data have limitations that make it difficult to assess how and why homelessness changed over our period of analysis. Although we used analytical techniques to help mitigate the effect of certain unobserved factors that were not included in our model, and performed tests to increase confidence in our results, there are a number of limitations associated with this econometric analysis and, as such, we interpret our model results with some degree of caution.⁴⁷ Our model shows an estimate of the relationship on average between changes in homelessness and any given factor for which we have data, and the possible range of this estimate. While the model shows an average association across the entire United States at the CoC level, the actual association may vary from locality to locality. Similarly, in instances where our model shows no relationship between a particular factor and homelessness, it may be because there is no discernable relationship on average even though that factor may be important in certain localities.⁴⁸

Our model consistently indicates that within CoCs, changes in household median rental prices and homelessness rate estimates were statistically

⁴⁶For our econometric model, we limited our analysis to years 2012 through 2018 due to improvements in PIT count data, accounted for merged CoCs, and applied statistical techniques and conducted sensitivity analyses to increase our confidence in the results. For example, we controlled for weather, which might affect the counts; controlled for available information on the methodology used for counting; and removed localities with unusual changes in year-to-year counts. Although the PIT count may not represent the exact number of homeless persons, 18 of 21 CoCs that we spoke to agreed that the PIT count generally reflected the trend of homelessness within their CoC.

⁴⁷We estimated the relationship between a variety of community-level factors and rates of homelessness using a weighted linear fixed-effects regression framework. We estimated several econometric models to ensure that our results were generally not sensitive to small changes in our model (for example, how or which variables influenced changes in rates of homelessness), including estimating models that compare total homelessness rates across rather than within CoCs. Despite the robustness of median rent in our results and our efforts to control for relevant factors, our results are subject to a number of caveats associated with this type of empirical analysis. For example, our regression models may be subject to omitted variable bias—it is unlikely that we have been able to quantify and include all factors relevant to homelessness. As such, we interpret these results with some degree of caution. See app. II for additional information.

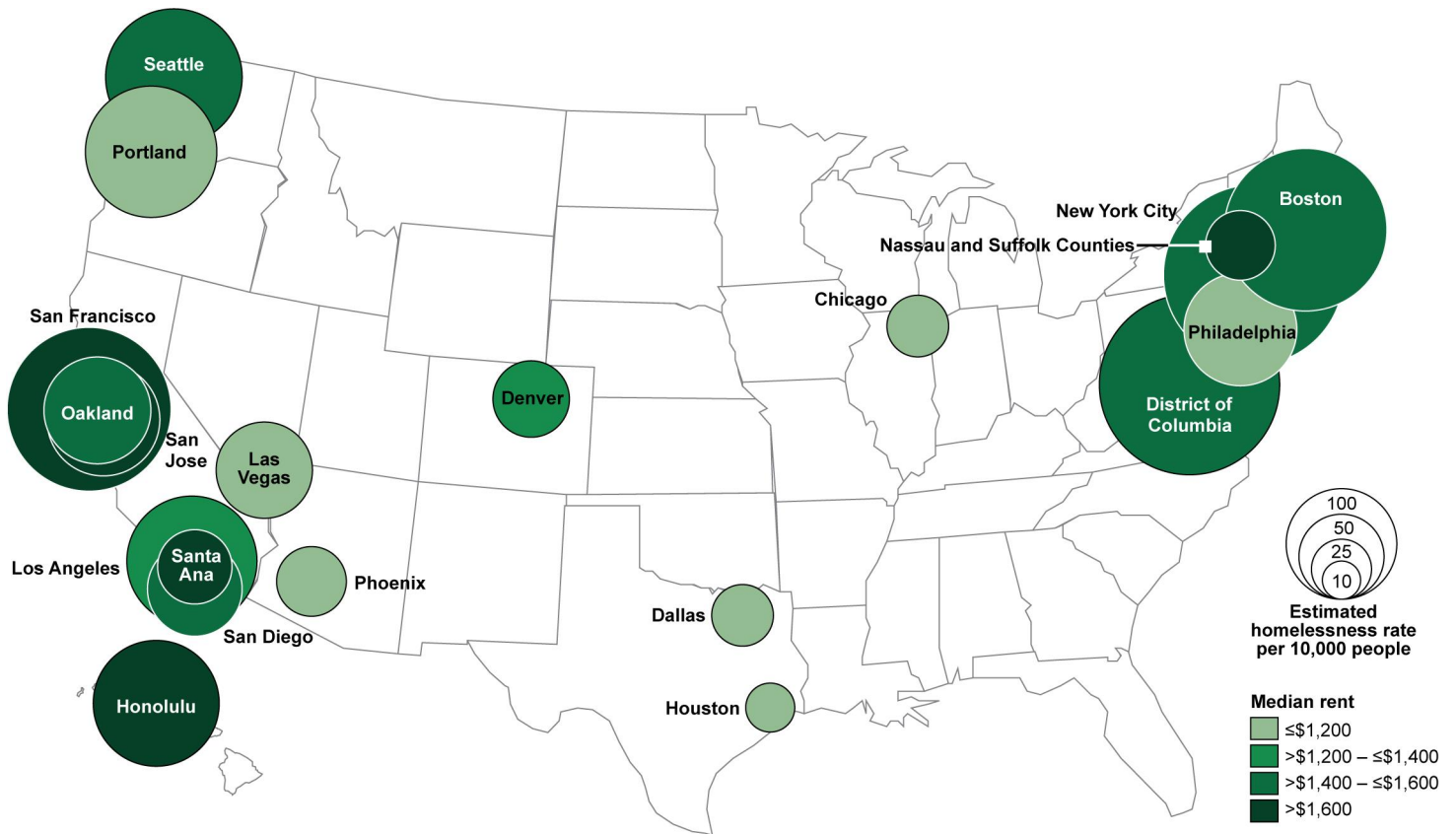
⁴⁸There are many other reasons a model might not corroborate a relationship where one may actually exist, such as insufficient variation in the variable of interest (particularly if the association is relatively minor), incorrect specification or functional form of the model, or collinearity with another variable.

significantly related over our period of analysis. Specifically, a \$100 increase in median rental price was associated with about a 9 percent increase in the estimated homelessness rate. For instance, in a CoC with a homelessness rate of 16 individuals per 10,000, a \$100 increase in household median rent would have an associated increase to about 17.4 individuals per 10,000.⁴⁹ In analyzing the relationship between rental prices and homelessness, we chose to model household median rental prices rather than the cost to obtain a new unit of housing, which might be somewhat higher than the median. Although the cost for a new mover to find housing would more closely reflect the experience of those attempting to exit homelessness, we chose to use household median rent prices because such a model more accurately reflects the experience of people for whom increasing rent is a factor that causes them to become homeless.⁵⁰ While the following geographic representation of the estimated homelessness rates and household median rents in CoCs with high PIT counts does not account for other factors that are controlled for in our model, it does show that these CoCs tend to have high rental prices and are concentrated along the East and West Coasts of the United States (see fig. 5).

⁴⁹We performed a variety of sensitivity analyses to increase our confidence in the results. For example, we removed localities with unusual changes in year-to-year counts and controlled for available information on the methodology used for counting, and the relationship between median rent and the homelessness rate remained positive and significant.

⁵⁰Additionally, we determined that rental data for new movers at the local level were less reliable than data on median rent.

Figure 5: Estimated Homelessness Rates and Median Household Rent in the 20 Largest Continuums of Care (CoC), 2018



Source: GAO analysis of Department of Housing and Urban Development and U.S. Census Bureau data. | GAO-20-433

Data table for Figure 5: Estimated Homelessness Rates and Median Household Rent in the 20 Largest Continuums of Care (CoC), 2018

Rank	CoC Number	CoC Name	2018 PIT Count (What We Used to Select Top 20)	2018 Median Rent (Used for Shading of Bubble)	Estimated Homelessness Rate per 10,000 People (Used for Bubble Diameter)
1	NY-600	New York City CoC	78,676	1409	94
2	CA-600	Los Angeles City & County CoC	49,955	1354	49
3	WA-500	Seattle/King County CoC	12,112	1413	54
4	CA-601	San Diego City and County CoC	8,576	1503	26
5	CA-500	San Jose/Santa Clara City & County CoC	7,254	2003	37
6	DC-500	District of Columbia CoC	6,904	1459	98

Letter

Rank	CoC Number	CoC Name	2018 PIT Count (What We Used to Select Top 20)	2018 Median Rent (Used for Shading of Bubble)	Estimated Homelessness Rate per 10,000 People (Used for Bubble Diameter)
7	CA-501	San Francisco CoC	6,857	1751	78
8	AZ-502	Phoenix, Mesa/Maricopa County CoC	6,298	1058	14
9	MA-500	Boston CoC	6,188	1454	77
10	NV-500	Las Vegas/Clark County CoC	6,083	1074	27
11	PA-500	Philadelphia CoC	5,788	994	37
12	CA-502	Oakland, Berkeley/Alameda County CoC	5,496	1585	33
13	IL-510	Chicago CoC	5,450	1069	11
14	CO-503	Metropolitan Denver CoC	5,317	1275	17
15	CA-602	Santa Ana, Anaheim/Orange County CoC	4,955	1734	16
16	HI-501	Honolulu City and County CoC	4,495	1693	46
17	TX-700	Houston, Pasadena, Conroe/Harris, Ft. Bend, Montgomery, Counties CoC	4,143	1056	7
18	TX-600	Dallas City & County, Irving CoC	4,121	1075	11
19	OR-501	Portland, Gresham/Multnomah County CoC	4,019	1121	50
20	NY-603	Nassau, Suffolk Counties CoC	3,868	1694	14

Note: This map represents the 20 CoCs with the largest point-in-time counts in 2018 excluding the balance of state CoCs, which include all the jurisdictions in a state that are not covered by any other CoC, and nonmetropolitan areas. We estimated 2018 homelessness rates because the U.S. Census Bureau data used for our analysis were available up to 2018 at the time of analysis and 2017 median rents (presented in 2018 dollars) to account for potential delayed impacts of rent on homelessness. Median household rent is the ACS's median gross rent, which is an estimate of the median share of rent and utilities paid by households across all unit sizes and types. Due to the fact that this measure calculates the median using actual rent paid by renters for occupied units with shared living situations rather than total rent for the entire unit, some localities, such as New York City, may appear to have lower rent than expected.

We also conducted structured interviews with representatives of 21 CoCs to better understand factors contributing to homelessness, including a variety of CoCs that had experienced increases, decreases, or very little change in their PIT counts from 2012 through 2018. Regardless of what the PIT count indicated, we asked representatives of the 21 CoCs questions about the most influential factors depending on what they stated was the trend of homelessness within their respective CoC. Eleven CoC representatives stated homelessness had increased in their CoC,

eight stated homelessness had decreased, and two stated it had remained relatively constant. Only three of the 21 disagreed with the trend in their CoC's PIT count. We also conducted semistructured interviews with local officials and homeless service providers during site visits and asked similar questions about factors related to homelessness.

Consistent with our model results, seven of the 11 CoC representatives that stated they experienced an increase in homelessness and several local officials and homeless service providers said they believed the cost of housing was one of the primary factors driving homelessness from 2012 through 2018. CoC representatives and others also said they believed the lack of affordable housing was a major related factor. One third of CoC representatives stated that a sizeable portion of their homeless populations held jobs and four of the 11 CoC representatives we interviewed that told us they experienced an increase in homelessness also cited low wages or wages not keeping up with increases in the cost of housing as a factor. All the CoC representatives that cited wages as a factor were urban or suburban. Many of the homeless service providers and local officials we interviewed also cited wages not keeping up with housing costs as a factor related to changes in homelessness.

Our model did not find a statistically significant relationship between wages and homelessness within CoCs. This result may be due to a lack of change in real wages during our period of analysis, or it may be that this relationship did not hold for the majority of CoCs. We would also anticipate homeless individuals to be in the lower end of the earnings distribution, and trends in income at the lower end of the distribution may be different from the median. As a result, the model may not capture the full relationship between wages and homelessness. Local officials and homeless service providers from some localities also stated that the value of housing vouchers or subsidies in their locality had remained largely unchanged or was not keeping up with the cost of housing, making it more difficult for people experiencing homelessness to find a place to live. Some of these officials and homeless service providers were also concerned about landlord discrimination toward those using vouchers.

Of the eight CoC representatives we interviewed that said they experienced a decrease in homelessness, four said they believed the decline was attributable to permanent supportive housing, rapid rehousing, or other related housing efforts. Half of these CoCs were suburban and half were rural. Rapid rehousing is an intervention designed to help individuals and families to quickly exit homelessness

and return to housing. It entails the following types of assistance, as needed by the individual or family and tailored to meet their needs: housing identification, rent and move-in assistance, and case management and services. Permanent supportive housing is permanent housing in which supportive services are provided to help individuals and families with a disability and experiencing homelessness to live independently. Our model did not corroborate a relationship between permanent housing supports (such as permanent supportive housing or vouchers) and homelessness.⁵¹

Of the eight CoC representatives that said they had experienced a decrease in homelessness, three stated that implementation of a coordinated entry system was a primary factor that led to the decline. All these CoCs were suburban or rural. As discussed earlier, coordinated entry creates a standardized assessment process and helps CoCs prioritize those who are most in need of assistance. According to HUD, the referral process for access to other resources is streamlined so that those seeking services can readily receive services and information.

Additional Economic Factors May Affect Changes in Homelessness, According to Local Stakeholders

Our econometric model is designed to explore economic and social factors thought to influence homelessness rates at the community level rather than individuals' likelihood of becoming homeless.⁵² The model did not include all potentially related factors because some data were unavailable at the local level or were difficult to measure for inclusion. Other community level factors that may be associated with homelessness and were included in the model did not produce a statistically significant relationship between the factor and homelessness rates, though this does not necessarily mean no such relationship exists. To complement our

⁵¹An academic paper examining the period from 2007 through 2014 found that increased housing support modestly reduced homelessness. Kevin Corinth, "The Impact of Permanent Supportive Housing on Homeless Populations," *Journal of Housing Economics*, vol. 35 (2017) p. 69–84.

⁵²For example, the model does not explore differences across individuals. In such a model, we could possibly examine mental health, family or criminal history, and other factors that might explain why some individuals are more likely to experience homelessness over others. Generally, the difference between a factor at the community level and at the individual level is in how it is measured. For instance, whether or not an individual has been evicted is at the individual level, but the rate of evictions across a CoC is at the community level.

empirical analysis, we conducted interviews with CoCs and other local stakeholders, including local officials and homeless service providers, and an academic literature search to qualitatively examine additional community and individual factors, such as the ones below that could potentially explain changes in homelessness. However, there may be other factors that influence homelessness that our interviews and literature search did not identify.

Poverty

Most CoC representatives we spoke with said they believed that poverty contributed to homelessness when asked specifically about poverty as a factor, but many described poverty influencing homelessness through its interaction with other factors, such as wages, job loss, or housing costs.⁵³ Only one CoC representative described poverty as a main factor contributing to homelessness. Poverty also appeared regularly in our search of academic literature. Our model did not show a statistically significant relationship between changes in poverty and homelessness within CoCs, which could possibly be due to insufficient variation in poverty rates to detect a relationship or a strong relationship between poverty and another variable.

Unemployment and Job Loss

Although CoC representatives generally did not mention unemployment as a main cause of changes in homelessness, approximately one-third of the 21 CoC representatives we interviewed said they believed that job loss was a common and direct cause of homelessness when asked about unemployment specifically. Some other CoC representatives told us they were either unsure about whether or not job loss was a common factor or believed that job loss is often one component of a longer path toward homelessness. For instance, one CoC representative stated that losing a job may force someone to take work for lower pay, which could ultimately cause them to fall behind on rent and thereby lead to eviction. Two CoC representatives said they believed that underemployment or reduction in

⁵³Following the Office of Management and Budget's Statistical Policy Directive 14, the Census Bureau uses a set of income thresholds that vary by family size and composition to determine who is in poverty. If a family's total income is less than the family's threshold, then that family and every individual in it is considered in poverty. The official poverty thresholds do not vary geographically, but they are updated for inflation using the Consumer Price Index. The official poverty definition uses money income before taxes and does not include capital gains or noncash benefits (such as public housing, Medicaid, and food stamps).

working hours contribute to homelessness because people are not making enough money to meet their needs or afford housing. Our model did not show a statistically significant relationship between changes in the unemployment rate and homelessness within CoCs.

Eviction

Six of the 21 CoC representatives we spoke to stated they believed that evictions were a factor contributing to homelessness, two believed that evictions were not a factor, and 12 CoC representatives were uncertain.⁵⁴ Among those CoC representatives that said evictions were a factor and those that were uncertain, several described eviction as an indirect cause because eviction is often the result of other circumstances, such as falling behind on rent payments due to job loss. A few CoC representatives and others described local programs that provide monetary or legal support for those facing eviction as having some effect in preventing people from becoming homeless. Some of the academic literature we reviewed also cited evictions as a factor related to homelessness. We did not model the effect of evictions on homelessness because of a lack of nationwide data.

Stakeholders Told Us Social Factors May Contribute to Becoming Homeless or Make It Harder to Exit Homelessness

Mental Health Challenges

CoC representatives, local officials, and homeless service providers described mental health challenges as a factor that can both lead to someone becoming homeless and make it more difficult to exit homelessness. Mental health was also frequently cited as a factor contributing to homelessness in our search of academic literature. We could not find a variable or multiple variables that accurately depicted the state of mental health within a CoC and, as such, we could not include mental health in our model. Further, the extent to which the state of mental health in the population has changed is unclear. As a result, we cannot be sure if mental health challenges are related to recent changes

⁵⁴One CoC representative provided a response in which it was unclear whether they were implying that evictions are or are not a factor. This CoC was not included in the above totals.

in homelessness or if they only helped determine baseline levels of homelessness.

Of the 11 CoC representatives that said homelessness had increased within their respective CoCs, three cited mental health challenges as one of the most influential factors. When asked specifically about mental health and substance use challenges, almost all of the 21 CoC representatives stated that within their respective CoCs, a significant number of homeless individuals were experiencing mental health challenges or substance use disorders. Many CoC representatives and homeless service providers described a lack of access to mental health care as driving continued homelessness. Some CoC representatives stated that they had lost providers of mental health services for homeless populations or that there were not enough providers. Other CoC representatives stated that there simply were not enough resources or funding for mental health services. Several CoC representatives stated that homeless people with untreated mental health or substance use challenges may face barriers to maintaining stable housing or employment and may not have access to stable social networks. Additionally, some CoC representatives and homeless service providers noted that it can be more difficult to assist homeless individuals with severe mental health challenges in finding or maintaining housing.

Although mental health challenges may contribute to other problems such as job loss or strained relationships with social networks, it is not always clear if someone has become homeless due to a mental health challenge or developed that challenge as a result of becoming homeless. Some CoC representatives emphasized that homelessness is extremely taxing on homeless individuals and may result in mental health challenges, particularly anxiety or depression, which can make it more difficult to exit homelessness.

Incarceration

Nineteen CoC representatives stated that it can be more difficult to find housing after being incarcerated. Twelve CoC representatives and several local officials and homeless service providers stated that landlords are reluctant to lease to someone who has been formerly incarcerated, and 10 other CoC representatives stated this difficulty may also apply to employment opportunities. For sex offenders, this reluctance can restrict where they can live even further. Some CoC representatives also stated that incarceration affects social support systems, and it may be difficult for those who have been incarcerated to rely on family or

friends for assistance. We could not include incarceration in our model due to the lack of a comprehensive source of data showing levels of incarceration at the local level. As a result, we are uncertain if incarceration is a factor affecting recent changes in homelessness or can only be used to help determine baseline levels of homelessness. However, based on CoC responses, incarceration may be a factor in determining the likelihood that any given individual becomes or remains homeless.

Domestic Violence

Domestic violence was cited as an influential factor contributing to homelessness by one CoC representative of the 11 that stated homelessness in their CoC had increased and was identified in our search of academic literature. We could not include domestic violence in our modeling, nor did we ask CoCs specifically about domestic violence, because CoCs are not required to collect data in their PIT counts on the number of people experiencing homelessness who reported that they were homeless because they were fleeing domestic violence. As a result, we are uncertain if domestic violence is a factor affecting recent changes in homelessness or if it can only be used to help determine baseline levels of homelessness. A service provider from one CoC stated that better education on homeless services may cause homeless counts to be slightly inflated because domestic violence victims may feel more comfortable escaping a domestic violence situation if they feel shelters are less stigmatized.

Other Factors May Potentially Be Related to Homelessness

Several other factors appeared to be potentially related to homelessness although they were not a focus of our analysis.

- **Overcrowding.** A 2019 HUD analysis found that the rate of overcrowding, measured by the share of housing units with more than 1.5 people per room, was a predictor of estimated total homelessness rates in urban areas.⁵⁵

⁵⁵2M Research, *Market Predictors of Homelessness: How Housing and Community Factors Shape Homelessness Rates Within Continuums of Care*, prepared for the U.S. Department of Housing and Urban Development (2019).

- **Racial demographics.** HUD has previously observed that people of color are overrepresented in homeless populations.⁵⁶ Although our models did not find a statistically significant relationship between racial demographic characteristics of CoCs and homelessness rates, this may be due to the fact that among the racial demographics that we included as control variables, there was relatively little variation within CoCs on average over our period of analysis.
- **Natural disasters.** Three CoCs stated that they believed their PIT count was affected by a recent hurricane. HUD officials agreed that natural disasters may be a local factor that contributes to homelessness.
- **Age.** A small number of CoCs, local officials, and homeless service providers mentioned that older individuals may be more vulnerable to becoming homeless, particularly when living on a fixed income. We did include the share of the population that is 65 or older in our model and did not find a statistically significant relationship, although there could be other factors related to aging that contribute to homelessness.

Conclusions

HUD's PIT count data show that the number of people experiencing homelessness in the United States increased for the third consecutive year in 2019. However, the PIT count data CoCs are required to report to HUD likely underestimate the number of persons experiencing homelessness and show unusual fluctuations that may not reflect true changes in the homeless population, particularly in unsheltered estimates. By evaluating data on CoCs' PIT count methodologies, improving instructions on the use of probability sampling techniques, and assessing assistance provided to CoCs, HUD would be better positioned to more accurately report the number of persons experiencing homelessness at the time of the PIT count. Assessing the assistance it provides to CoCs would also enable HUD to further improve the quality of information collected through HMIS databases and the Housing Inventory Count. Without data that better reflect the true size and characteristics of the homeless population, HUD and policymakers are limited in their ability

⁵⁶The 2017 Annual Homeless Assessment Report (AHAR) to Congress Part 2, prepared by the U.S. Department of Housing and Urban Development (2018).

to accurately identify and appropriately respond to changes in the number of persons experiencing homelessness.

Recommendations for Executive Action

We are making the following three recommendations to HUD:

HUD's Office of Special Needs Assistance Programs should conduct quality assurance checks on the PIT count methodology data it requires CoCs to submit and take actions as appropriate to ensure that HUD's standards for conducting valid and reliable PIT counts are met. (Recommendation 1)

HUD's Office of Special Needs Assistance Programs should provide more detailed instructions on using probability sampling techniques to complete the PIT count, such as by updating its *Point-in-Time Count Methodology Guide* to instruct CoCs on reporting measures of error and bias in PIT count results. (Recommendation 2)

HUD's Office of Special Needs Assistance Programs should assess and enhance the usefulness of its assistance to CoCs' data collection efforts. (Recommendation 3)

Agency Comments

We provided a draft of this report to HUD and USICH for comment. In its written comments, reproduced in appendix VI, HUD concurred with our recommendations and cited actions to address them. HUD and USICH both provided technical comments, which we incorporated as appropriate.

We also provided a draft of the relevant appendix to the Departments of Education and Veterans Affairs for their review and comment. VA provided technical comments, which we incorporated as appropriate.

As agreed with your office, unless you publicly announce the contents of this report earlier, we plan no further distribution until 30 days from the report date. At that time, we will send copies of this report to the Secretary of Housing and Urban Development, Secretary of Education, Secretary of Veterans Affairs, Executive Director of the U.S. Interagency Council on Homelessness, and other interested parties. In addition, the

report will be available at no charge on GAO's website at <http://www.gao.gov>.

If you or your staff have any questions about this report, please contact me at (202) 512-8678 or cackleya@gao.gov. Contact points for our Offices of Congressional Relations and Public Affairs are listed on the last page of this report. GAO staff who made major contributions to this report are listed in appendix VII.

Sincerely yours,

A handwritten signature in black ink that reads "Alicia Puente Cackley". The signature is written in a cursive style with a large initial 'A'.

Alicia Puente Cackley
Director, Financial Markets and Community Investment

Appendix I: Objectives, Scope, and Methodology

The objectives of this report were to examine (1) efforts to measure homelessness and the Department of Housing and Urban Development's (HUD) oversight of these efforts and (2) factors related to recent changes in homelessness.

To address both objectives, we analyzed policies and procedures for data collection and reporting by HUD grantees known as Continuums of Care (CoC) that manage local homelessness response systems. We also reviewed laws and administrative rules governing the CoC program; manuals describing HUD data systems; and HUD Annual Homelessness Assessment Reports submitted to Congress for 2012–2018. We interviewed HUD headquarters officials from the Office of Special Needs Assistance Programs, which oversees the administration of the CoC program and other programs with a role in homelessness assistance, and the Office of Community Planning and Development. We met with officials of the U.S. Interagency Council on Homelessness (USICH) to discuss homelessness assistance programs and data across its 19 federal member agencies. We also interviewed officials and staff from the National Alliance to End Homelessness and the National Law Center on Homelessness and Poverty to obtain their perspectives on homelessness data collection and factors affecting changing levels of homelessness. Additionally, we conducted literature searches (discussed below) to identify studies or reports related to homelessness data collection and factors affecting homelessness levels.

To address our first objective to examine efforts to measure homelessness and HUD's oversight of these efforts, we evaluated nine methodologies used by federal agencies to collect information on homeless populations. We selected methodologies used to collect data on the size of the U.S. homeless population or key subpopulations, and the geographic distribution of homelessness in the United States. These methodologies included HUD's Point-in-Time (PIT) count, Homeless Management Information System (HMIS), and Housing Inventory Count, among others. We also selected the Education for Homeless Children and Youth (EHCY) dataset administered by the Department of Education (Education) and the Homeless Operations Management and Evaluation System (HOMES) dataset administered by the Department of Veterans

Affairs (VA).¹ We provide information on HOMES and EHCY in appendix III.

We obtained and analyzed PIT count data for 2007 through 2019, Housing Inventory Count data for 2007 through 2018, HMIS data for 2009 through 2017, EHCY data for school year 2013–2014 through school year 2016–2017, and HOMES data for 2012 through 2018. We assessed the reliability of these data by reviewing data collection standards issued by the agencies and system documentation, interviewing officials knowledgeable about system controls, and conducting electronic testing of each data set. Because the scope of each data source is different, our electronic testing did not include comparisons between HUD’s three data sources. We searched for peer-reviewed studies and reports, among other types of publications, published from 2000 through 2018 on federal homelessness counts, their limitations, and proposals for improving the accuracy and reliability of the counts within our scope. We reviewed and summarized 44 papers relevant to the first objective.

We determined that the PIT count data did not provide a reliably precise estimate of homeless individuals but were adequate for the purposes of conducting trend analysis and inclusion in econometric models (discussed later in this section and in app. II) after we applied statistical techniques and sensitivity analyses to increase our confidence in the results. Although we obtained PIT count data for 2007–2019, we limited our trend analysis to 2012–2019 and our econometric analysis to 2012–2018 because data from the later time frame were more reliable due to improvements in PIT count data over time.² We also applied statistical techniques to improve the reliability of the PIT count data in the model, such as controlling for weather that might affect the counts. Moreover, we performed other sensitivity analyses to increase our confidence in the results. For example, we removed localities with unusual changes in year-to-year counts and controlled for available information on the methodology used for counting. The HMIS and Housing Inventory Count

¹In addition to the HUD, VA, and Education data sources selected, we considered the following data sources but excluded them from our scope of review: Education’s Free Application for Federal Student Aid data; VA’s Homelessness Screening Clinical Reminder data; the U.S. Census Bureau’s Service-Based Enumeration data; and the Department of Health and Human Services’ Head Start program data. These data sources do not provide annual or biennial data on the full homeless population or key subpopulations.

²Data from HUD’s 2018 PIT count were the most recent available at the time we began the process of conducting our econometric analysis.

data were generally complete and reliable. We took the same steps to assess the EHCY and aggregated HOMES data, and we determined that both were generally complete and reliable.

To obtain information about the extent to which reliable, accurate data are being collected by CoCs, we conducted four focus groups by videoconference with officials from a nongeneralizable, randomly selected sample of 34 CoCs. The officials are responsible for collecting data on homelessness within their jurisdictions and reporting these data to the federal government. Two groups discussed the PIT count and Housing Inventory Count and the other two discussed the HMIS system. The selection of localities was stratified by characteristics including CoC geographic size based on HUD's Annual Homeless Assessment Report size classifications, geographic distribution within HUD regions, and PIT methodology type. To conduct a content analysis of the focus group responses, we developed a list of relevant themes and topics discussed during the focus groups. Using the list, two analysts independently coded the compiled focus group responses, and then reconvened to resolve coding discrepancies. Because we selected a nonprobability sample of CoCs, the information we obtained from our interviews cannot be generalized more broadly to all CoCs. See appendix IV for a full list of CoCs included in our focus groups.

To help assess the quality of federal homelessness data, we completed 12 structured interviews with homelessness researchers who are experts on federal homelessness counts, have conducted quantitative work using data from these counts, and were able to describe known limitations of these counts. We selected the researchers we interviewed judgmentally using the results of our literature search to identify researchers who had done prior work on homelessness measurement. We also identified researchers based on recommendations from agency officials or other researchers. We developed a structured interview instrument that included questions on the five datasets within our scope, and we pretested our instrument by obtaining feedback on the clarity of our interview questions from three homelessness researchers who did not participate in our structured interviews. We used a word-enabled questionnaire to record responses during interviews. We analyzed the compiled results and documented responses that were mentioned by at least two different researchers. The researchers may not represent all views on topics discussed, but their expertise provided insights on federal homelessness data. See appendix V for a full list of the researchers we interviewed. We assessed HUD's guidance and oversight of homelessness data collection against HUD's *Point-in-Time Count*

Methodology Guide, CoC program interim rule, federal internal control standards, and federal standards for statistical surveys.³

To identify factors that appear to have influenced changes in homelessness from 2012 through 2018, we conducted multiple regression analyses using data from the PIT count; population estimates from the U.S. Census Bureau; housing, demographic, and economic data from the U.S. Census Bureau's American Community Survey, the U.S. Census Bureau Small Area Income and Poverty Estimates, the Bureau of Labor Statistics Local Area Unemployment Statistics, and HUD's Housing Inventory Count; housing assistance, CoC award, and PIT Count methodology data; and weather data from the National Oceanic and Atmospheric Administration. The factors we examined were chosen based on data availability and a review of academic literature examining homelessness. We focused on peer reviewed studies from 2000 through 2019. For our review of academic literature, we counted the frequency with which a given factor was described as contributing to homelessness to identify factors for inclusion in our model. Given the difficulty of counting the population experiencing homelessness, we used a variety of methods to increase confidence that results were not driven by factors that might affect homelessness counts but not the actual number of homeless persons. Our work was designed to assess whether there were discernable relationships between the factors we identified and homelessness, but we did not seek to identify a causal link. Appendix II provides detailed information on our regression analyses, data sources, results, and limitations.

In addition, we conducted structured interviews with 21 CoCs on how homelessness had changed in their communities in recent years, and the factors to which they attributed to the changes. These CoCs included the New York City and Los Angeles City and County CoCs, which were selected because they contain, by a significant amount, the largest homeless populations in the country. We also conducted a structured interview with the Colorado Springs CoC as part of a site visit. The other 18 CoCs were selected through a stratified sample to provide geographic diversity among 10 HUD regions and size diversity within urban, suburban, and rural CoCs. We conducted a literature search to identify factors associated with changes in homelessness to include in our structured interview instrument. We also asked CoC participants closed-

³GAO, *Standards for Internal Control in the Federal Government*, [GAO-14-704G](#) (Washington, D.C.: Sept. 10, 2014). Office of Management and Budget, *Standards and Guidelines for Statistical Surveys* (Washington, D.C.: 2006). 24 C.F.R. Part 578.

ended and open-ended questions about the accuracy of their PIT count results, and what they viewed as the most influential factors affecting changing levels of homelessness. We developed and pretested a structured interview instrument and we used a word-enabled questionnaire to record responses during interviews. We analyzed the compiled results and documented responses. See appendix IV for a full list of CoCs selected for structured interviews.

To gather perspectives on the factors affecting homelessness, we visited a nonprobability sample of three CoCs in New York, New York; Colorado Springs, Colorado; and Los Angeles, California. We selected CoCs that contained major cities as classified by HUD because they were more likely than rural or suburban areas to have a variety of homeless service providers.⁴ We also selected CoCs that had experienced an increase in homelessness during the years within the scope of our review and that were located in different HUD regions.⁵ At each site, we conducted semistructured interviews with CoC representatives (13 individuals across all sites), local government officials (18 individuals across all sites), and homeless service providers (19 individuals across all sites). Following each site visit, we conducted semistructured interviews with the USICH regional coordinator responsible for that locality.

We conducted this performance audit from March 2018 to July 2020 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

⁴HUD has classified CoCs representing the 50 most populous cities in the United States in the major city CoC category.

⁵We compared the percentage change in the PIT count in the CoC to the percentage change in population to determine if some locations may have experienced a PIT increase proportional to the CoC's total population. We then selected three site visit locations that had experienced the largest percentage change in the PIT count from 2012 through 2018 that was not proportional to increases in population.

Appendix II: Description of and Results for GAO's Econometric Model of Factors That May Influence Homelessness

Introduction

This appendix describes the analyses we conducted to assess the relationship between a variety of factors and rates of homelessness at the Continuum of Care (CoC) level and by years for 2012 through 2018.¹ The factors we examined were chosen based on our review of the literature and data availability. We used data from a variety of sources, such as point-in-time (PIT) homelessness counts from the Department of Housing and Urban Development (HUD); housing, demographic, and economic characteristics from the U.S. Census Bureau; and housing assistance and funding data from HUD, among others. Specifically, we combined data from the different sources and aggregated them at the CoC and year level to estimate the average relationship between the different factors and rates of homelessness within communities in a fixed-effects regression framework.²

Given the difficulty of counting the population experiencing homelessness, we used a variety of methods to increase confidence that results were not driven by factors that might affect homelessness counts—such as controlling for the weather on the day of the PIT count, controlling for methodological differences that could affect the PIT count across CoCs and over time, and excluding CoCs that had large fluctuations in homelessness rates during our study period as part of the sensitivity analysis. Moreover, according to HUD officials, the PIT count data have become more reliable over time, particularly after 2011, and

¹Throughout this analysis we define the homelessness rate as the count of individuals experiencing homelessness, according to the Department of Housing and Urban Development's point-in-time count, per 10,000 people.

²To analyze the relationship as validly as the available data and data constraints allowed, we explored various panel data modeling techniques and determined that the fixed-effects framework was more appropriate to control for various omitted variables biases.

results from electronic testing of the data showed that large year-over-year fluctuations were less likely to occur after 2012. Thus, we limited our analysis to 2012 through 2018.³

Prior studies that examined the relationship between different factors and homelessness by looking at communities over time found a positive relationship between homelessness and rental prices, as well as modest negative effects of permanent supportive housing on homelessness rates. However, the studies use data from before 2018.⁴ Our work was designed to assess whether there were discernable relationships between each factor we identified and homelessness rates from 2012 through 2018 while holding other factors fixed, including CoC and year fixed effects, but not to identify a causal link between the factors and homelessness. This appendix discusses (1) data sources and basic model structure, (2) results, and (3) caveats.

Data Sources and Basic Model Structure

Data Sources

Our analysis is based on a panel of CoCs for 2012 through 2018 such that each observation corresponds to a CoC in a given year. The sample

³For example, 3.9 percent of the observations had a change of more than 50 percent in the total count after 2012 compared to 6 percent of the observations before 2012, and this difference is statistically significant. Looking at sheltered and unsheltered counts separately, large fluctuations were also less likely to occur after 2012 for sheltered counts but not for the unsheltered counts.

⁴Two of these studies use data for 2007 through 2014 in a fixed-effects framework. The other two studies use more recent data, 2011 through 2016 and 2011 through 2017. One looked at the largest metro areas, and the other was a nationwide study designed to identify inflection points in poverty and housing affordability associated with a rapid growth in homelessness, but these two newer studies only directly examine a limited set of factors (i.e. rental prices, income and poverty). See Kevin Corinth, "The Impact of Permanent Supportive Housing on Homeless Populations," *Journal of Housing Economics*, vol. 35 (2017) p. 69–84; Chris Glynn and Emily B. Fox, *Dynamics of Homelessness in Urban America* (2017); Chris Glynn, Thomas H. Byrne, and Dennis P. Culhane, *Inflection Points in Community-Level Homeless Rates* (2018); and Maria Hanratty, "Do Local Economic Conditions Affect Homelessness? Impact of Area Housing Market Factors, Unemployment, and Poverty on Community Homeless Rates," *Housing Policy Debate*, vol. 27, no. 4 (2017).

consists of 384 CoCs for which there were data for all years during the period.⁵ Specifically, the data used include the following:

- **CoC homelessness counts.** The homelessness count data are from HUD's PIT estimate. The PIT count is a count of sheltered and unsheltered homeless persons on a single night in January. HUD requires that CoCs conduct a biennial count of homeless persons who are sheltered in emergency shelter, transitional housing, and safe haven projects on a single night.⁶ CoCs also must conduct a count of unsheltered homeless persons every other year (odd numbered years), though a majority of the CoCs conducted unsheltered counts every year from 2013 through 2018 (specifically, 79 percent, 86 percent and 87 percent conducted sheltered and unsheltered counts in 2014, 2016 and 2018, which were off years).⁷ The data are reported to and compiled by HUD. We focus primarily on the aggregate variable from the PIT count database (i.e., the total homelessness counts). These data are available at the CoC and year level.
- **Housing characteristics.** Housing characteristics come from the U.S. Census American Community Survey (ACS) 5-year estimates. These include median rent, rental vacancy rate, and the share of renter-occupied units.⁸ These data are available at the county and year level.

⁵After accounting for mergers (i.e., if a CoC merged with another CoC at any point during the period we added up the count of homeless individuals before the period to the post-merger CoC), there were 399 unique CoCs in the original dataset from 2012 through 2018. We excluded 11 CoCs for which we did not have data for every year as well as those in Puerto Rico, Guam and the Virgin Islands. Our sample of 384 CoCs accounts for 99 percent of the total homelessness count for 2012 through 2018.

⁶A safe haven is a form of supportive housing that serves hard-to-reach homeless persons with severe mental illness who come primarily from the streets and have been unable or unwilling to participate in housing or supportive services.

⁷When they submit their PIT count data to HUD, CoCs report information about the methodologies they used. In off years, this includes reporting whether they completed a sheltered count only or both an unsheltered and sheltered count. HUD provided us these reports for 2013 through 2018.

⁸Median rent is for gross rent, which is the contract rent plus the estimated average monthly cost of utilities (electricity, gas, and water and sewer) and fuels (such as oil, coal, kerosene, or wood) if these are paid by the renter (or paid for the renter by someone else). Gross rent is intended to eliminate differentials that result from varying practices with respect to the inclusion of utilities and fuels as part of the rental payment.

- **Demographic characteristics.** Total population estimates come from the U.S. Census Bureau population estimates and demographic characteristics come from the ACS 5-year estimates. Demographic characteristics include individuals 65 years of age or older, veterans, African Americans, Latinos, and family households where the head of household is a single parent. These data are available at the county and year level.
- **Economic characteristics.** Economic characteristics come from the ACS 5-year estimates and include the unemployment rate, Supplemental Nutrition Assistance Program (SNAP) recipients, cash public assistance recipients, people in poverty, social security income recipients, and median earnings. These variables are available by county and year.⁹
- **Funding.** Data on the number of available beds by CoC and year come from HUD's Housing Inventory Count, which includes the number of beds for emergency shelter/transitional housing/safe haven projects, permanent supportive housing, rapid rehousing, and other permanent supportive housing. We also used HUD data on the number of people receiving housing support by county and year.¹⁰ Finally, we used HUD data on CoC award amount by CoC and year.¹¹
- **Matching of county-level data to CoC-level data.** Because PIT count data are reported at the CoC level, we had to create CoC-level measures of the independent variables that were at the county level. We used a two-step process. First, we mapped counties to CoCs and assigned a county to a CoC if the county centroid fell inside the CoC

⁹We also used poverty rates from the U.S. Census Bureau Small Area Income and Poverty Estimates and unemployment rates from the Bureau of Labor Statistics Local Area Unemployment Statistics instead of the ACS estimates for these variables in sensitivity analysis. The U.S. Census Bureau Small Area Income and Poverty Estimates are estimated using Internal Revenue Service tax return data as well as SNAP and ACS data.

¹⁰Subsidized housing data cover housing assistance provided under public housing (a form of project-based housing), tenant-based assistance (i.e., Housing Choice Voucher Program), and project-based assistance.

¹¹CoC awards fund local homeless housing and service projects. Awards are for projects that fall under a variety of program components—for example, CoC planning grants, the Homeless Management Information System (HMIS), permanent housing, rapid rehousing, safe havens, supportive services, and transitional housing, among others.

boundary.¹² Second, we aggregated these county-level measures at the CoC level by taking the population-weighted average of each measure, with counties with larger populations getting a higher weight in the CoC-level measure. To estimate the homeless count rate in a given CoC, we aggregated the population estimates for each county assigned to the CoC.¹³

Summary Statistics

Table 4 shows the summary statistics for each variable included in the main analysis.

¹²Centroid is the term given to the center of an area, region, or polygon. In the case of irregularly shaped polygons, the centroid is derived mathematically to approximate a center.

¹³In sensitivity analysis, we further controlled for variables that might affect the population captured by the count. Specifically, to control for methodological changes which might affect the count, we controlled for indicators for the methodology used (such as whether the sheltered count was done using observation, whether HMIS was used, or whether the unsheltered count was service based). This information was available by CoC and year but only for 2013 and later. Also, we heard from CoCs that weather on the day of the count could affect the count; for example, CoC focus group participants told us that a snow storm on the day of the PIT count can affect the results. Thus, to control for weather on the day of the PIT count, we used National Oceanic and Atmospheric Administration weather data by station and day, including precipitation and snow accumulation and minimum temperature. The station-level variables were aggregated at the county level by taking the average for the stations in the county for a given day. Once we had the county level measures, we created CoC-level measures by taking the population-weighted average for counties for which there were data.

A county can fully overlap with a CoC or with only a portion of a CoC. Thus, as sensitivity analysis, we re-ran the analysis where counties were assigned to a CoC based on land overlap. First we dropped counties that had less than a 5 percent land overlap with any given CoC and then kept only CoCs where all remaining counties that overlapped them did so by more than 75 percent. Note that the majority of counties have more than a 75 percent land overlap with a given CoC. Specifically, for about 94 percent of the CoCs, all of the counties that overlap them do so by more than 75 percent. The disadvantage of this analysis is that it does not include all CoCs.

In the main analysis we used ACS 5-year estimates and used ACS 1-year estimates in sensitivity analysis. ACS 5-year estimates cover all counties and are 5-year rolling averages. ACS 1-year estimates are current annual estimates and thus might exhibit more variation than the 5-year estimates, but are only available for areas with populations of more than 65,000. Thus for sensitivity analysis with ACS 1-year estimates we calculated the CoC-weighted average only of the counties for which there were data.

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Table 4: Summary Statistics for Variables Used in GAO's Regression Analyses of Factors That May Influence Homelessness, 2012–2018

Variable	Definition	Source	Mean	Standard Deviation
Total homelessness rate	Total homelessness point-in-time (PIT) count per 10,000 population	Department of Housing and Urban Development (HUD) PIT/U.S. Census Bureau population estimates	17.73	18.67
Median rent (2018 dollars)	Median gross rent (in 2018 dollars)	U.S. Census Bureau American Community Survey (ACS)	983.21	264.95
Rental vacancy rate	Vacancy rate for rental units	U.S. Census Bureau ACS	6.92	2.81
Renter occupied (%)	Percentage of units that are renter occupied	U.S. Census Bureau ACS	34.02	8.37
Black or African American (%)	Percentage of the population that is Black or African American	U.S. Census Bureau ACS	11.72	11.84
Hispanic or Latino origin (%)	Percentage of the population that is of Hispanic or Latino origin	U.S. Census Bureau ACS	12.44	13.05
Age 65+ (%)	Percentage of the population age 65 or older	U.S. Census Bureau ACS	14.40	3.49
Veterans (%)	Percentage of the population that are veterans	U.S. Census Bureau ACS	9.32	2.80
Single-parent households (%)	Percentage of single-parent households	U.S. Census Bureau ACS	33.27	7.78
Unemployment rate	Percentage of the population that are unemployed out of the total civilian labor force	U.S. Census Bureau ACS	5.26	1.41
Supplemental Nutrition Assistance Program (SNAP) recipients (%)	Percentage of the households receiving food stamps/SNAP assistance	U.S. Census Bureau ACS	11.98	4.55
Cash public assistance recipients (%)	Percentage of the households receiving cash public assistance	U.S. Census Bureau ACS	2.77	1.25
Poverty (%)	Percentage of people whose income falls below the poverty line	U.S. Census Bureau ACS	14.66	4.67
Social security income recipients (%)	Percentage of households receiving social security income	U.S. Census Bureau ACS	30.16	6.21
Median earnings (2018 dollars)	Median earnings for workers (in 2018 dollars)	U.S. Census Bureau ACS	33304.90	6872.84
Housing Inventory Count total bed count rapid rehousing/permanent supportive housing/other permanent housing	Housing Inventory Count total number of beds for rapid rehousing, permanent supportive housing and other permanent housing per 10,000 population	HUD/U.S. Census Bureau Population Estimates	11.46	14.45

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Variable	Definition	Source	Mean	Standard Deviation
Housing Inventory Count total bed count emergency shelter/transitional housing/safe haven rate	Housing Inventory Count total number of beds for emergency shelter, transitional housing and safe haven per 10,000 population	HUD/U.S. Census Bureau Population Estimates	12.67	11.77
Continuum of Care (CoC) award (2018 dollars) per capita	HUD CoC award amount (in 2018 dollars) per capita	HUD/U.S. Census Bureau Population Estimates	5.76	6.41
Rate of people receiving housing support	Total number of people receiving supportive housing per 10,000 population	HUD/U.S. Census Bureau Population Estimates	229.76	190.91

Source: GAO analysis of data from the U.S. Census Bureau and the Department of Housing and Urban Development. | GAO-20-433

Notes: The sample size is N=2,688 and includes 384 CoCs for which there were data for every year from 2012 through 2018. Mean and standard deviation are for the CoC-level variables used in the model, which are weighted averages of county-level data for variables not available at the CoC level and are lagged, except for the total homelessness rate, which is for the current year. Housing, demographic and economic characteristics are based on the ACS 5-year estimates. Median rent, median earnings, and CoC awards are adjusted for inflation and expressed in 2018 dollars using the Consumer Price Index from the U.S. Department of Labor, Bureau of Labor Statistics.

Model Structure

We estimated the relationship between a variety of community-level factors and rates of homelessness using a weighted linear fixed-effects regression framework. Specifically, the main estimation equation is as follows:

$$\ln(\text{homeless rate}_{ct}) = \alpha + \beta_1 H_{ct-1} + \beta_4 D_{ct-1} + \beta_2 Econ_{ct-1} + \beta_3 Fund_{ct-1} + \delta_t + \gamma_c + \epsilon_t$$

$\ln(\text{homeless rate}_{ct})$ is the natural log of the homelessness rate per 10,000 people for CoC c in year t , defined as the total homeless PIT count in the CoC divided by total population. Note that because the count is done in January, the factors are for the year prior to the count. The other variables are as follows:

- H_{ct-1} is a set of housing characteristics that include median rent in 2018 dollars, the share of the rental units that were vacant, and the

percentage of units that were renter occupied for CoC c in the year prior to the count.¹⁴

- D_{ct-1} is a set of demographic characteristics for CoC c in the year prior to the count that include the percentage of the population that was African American, Hispanic, 65 years of age or over, or veteran, and the percentage of single-parent households.
- $Econ_{ct-1}$ is a set of economic characteristics for CoC c in the year prior to the count that include the unemployment rate, the percentage of people receiving SNAP assistance, the percentage of people receiving cash public assistance, the percentage of people living in poverty, the percentage of households with social security income, and median earnings for workers in 2018 dollars.¹⁵
- $Fund_{ct-1}$ is a set of funding variables for CoC c in the year prior to the count that include the rate of bed coverage per 10,000 people under emergency shelter/temporary housing/safe haven and under permanent supportive housing/rapid rehousing/other permanent supportive housing, CoC per capita award amount in 2018 dollars, and the number of individuals living in subsidized housing per 10,000 people.¹⁶

Finally, δ_t is a set of year fixed effects that control for national shocks that affect all CoCs, such as interest rates, and γ_c is a set of CoC fixed effects that control for CoC characteristics that do not change over time, such as permanent housing policies (e.g., rent control or eviction ordinances or laws). ϵ_t is the error term. The standard errors are clustered at the CoC level in order to account for serial correlation in the homelessness rate for a given CoC over time. Following prior literature, regressions are weighted by the average population during the period. Given that larger areas tend to have a larger number of people experiencing homelessness, these areas might be more representative of the typical

¹⁴Median rent was adjusted for inflation and expressed in 2018 dollars using the Consumer Price Index from the U.S. Department of Labor, Bureau of Labor Statistics. Note that although in this appendix we refer to housing and economic characteristics separately, in the report we consider housing characteristics a subset of economic characteristics.

¹⁵Median earnings were adjusted for inflation and expressed in 2018 dollars using the Consumer Price Index from the U.S. Department of Labor, Bureau of Labor Statistics.

¹⁶CoC award amounts were adjusted for inflation and expressed in 2018 dollars using the Consumer Price Index from the U.S. Department of Labor, Bureau of Labor Statistics.

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experience for individuals experiencing homelessness. However, we also tested the sensitivity of our analysis to not using population weights by running the model where these weights are omitted.

Results

Table 5 presents estimates of the relationship between rates of homelessness and a variety of factors, such as housing and economic characteristics. The first column shows the regression of housing characteristics on rates of homelessness while only controlling for CoC and year fixed effects. Thus, this is the relationship between housing characteristics and homelessness rates within communities without controlling for other factors. Columns (2) through (4) further control for additional sets of factors that fall under demographic characteristics, economic characteristics, and funding, respectively.

Table 5: Results of Regression Analyses of CoC-Level Rates of Homelessness and Factors, 2012–2018

Dependent variable: log (total homelessness rate)	(1)	(2)	(3)	(4)
Median rent (2018 dollars)	0.00086**	0.00076**	0.00100***	0.00087**
Median rent (2018 dollars) (total homelessness rate)	(0.00037)	(0.00037)	(0.00037)	(0.00036)
Rental vacancy rate	0.01199	0.00895	0.00953	0.00685
Rental vacancy rate (total homelessness rate)	(0.01654)	(0.01434)	(0.01588)	(0.01376)
Renter occupied (%)	-0.07795***	-0.08286***	-0.09361***	-0.06625***
Renter occupied (%) (total homelessness rate)	(0.02577)	(0.02413)	(0.02315)	(0.02029)
Black or African American (%)	--	0.04089	0.04260	0.03749
Black or African American (%) (total homelessness rate)	--	(0.03917)	(0.03803)	(0.03154)
Hispanic or Latino origin (%)	--	0.01405	-0.00575	0.00530
Hispanic or Latino origin (%) (total homelessness rate)	--	(0.03277)	(0.03306)	(0.03237)
Age 65+ (%)	--	-0.01941	-0.05789	-0.06295
Age 65+ (%) (total homelessness rate)	--	(0.03755)	(0.05037)	(0.04825)
Veterans (%)	--	0.01964	-0.01047	-0.03463
Veterans (%) (total homelessness rate)	--	(0.06859)	(0.06638)	(0.06288)
Single-parent households (%)	--	-0.01018	-0.01548	-0.01246
Single-parent households (%) (total homelessness rate)	--	(0.01143)	(0.01083)	(0.00939)
Unemployment rate	--	--	-0.00591	-0.00131
Unemployment rate (total homelessness rate)	--	--	(0.03052)	(0.02767)
Supplemental Nutrition Assistance Program recipients (%)	--	--	0.03541**	0.02612*
Supplemental Nutrition Assistance Program recipients (%) (total homelessness rate)	--	--	(0.01424)	(0.01386)
Cash public assistance recipients (%)	--	--	-0.01743	-0.02544

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Dependent variable: log (total homelessness rate)	(1)	(2)	(3)	(4)
Cash public assistance recipients (%) (total homelessness rate)	--	--	(0.02736)	(0.02653)
Poverty (%)	--	--	0.00418	0.00024
Poverty (%) (total homelessness rate)	--	--	(0.02769)	(0.02492)
Social Security Income recipients (%)	--	--	0.02223	0.03235
Social Security Income recipients (%)	--	--	(0.02684)	(0.02607)
Median earnings (2018 dollars)	--	--	-0.00002	-0.00002
Median earnings (2018 dollars) (total homelessness rate)	--	--	(0.00002)	(0.00002)
Housing Inventory Count total bed count (rapid rehousing/permanent supportive housing/other permanent housing rate)	--	--	--	0.00126
Housing Inventory Count total bed count (rapid rehousing/permanent supportive housing/other permanent housing rate) (total homelessness rate)	--	--	--	(0.00118)
Housing Inventory Count total bed count (emergency shelter/transitional housing/safe haven rate)	--	--	--	0.01550***
Housing Inventory Count total bed count (emergency shelter/transitional housing/safe haven rate) (total homelessness rate)	--	--	--	(0.00254)
Continuum of Care (CoC) award (2018 dollars) per capita	--	--	--	0.01268
Continuum of Care (CoC) award (2018 dollars) per capita (total homelessness rate)	--	--	--	(0.00777)
Total people receiving housing support rate	--	--	--	0.00034
Total people receiving housing support rate (total homelessness rate)	--	--	--	(0.00041)
Constant	4.21948***	4.15508**	5.24957**	3.96269*
Constant (total homelessness rate)	(1.05299)	(1.66846)	(2.12544)	(2.07887)
Observations	2,688	2,688	2,688	2,688
R-squared	0.28776	0.29273	0.30567	0.33736
Number of CoCs	384	384	384	384
CoC fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

Legend:

* = significantly different from zero at 90 percent confidence level; ** = significantly different from zero at the 95 percent confidence level; *** = significantly different from zero at the 99 percent confidence level.

Source: GAO analysis of data from the U.S. Census Bureau and the Department of Housing and Urban Development. | GAO-20-433

Notes: The dependent variable is the natural log of the total homelessness rate, defined as the total homelessness point-in-time count per 10,000 people. Independent variables are for the year prior to the count. Regressions are weighted by the average population over the period of analysis. The reported R-squared is the within R-squared. Standard errors clustered at the CoC level are in parentheses.

As shown in table 5, of the housing variables, median rent is consistently positively and statistically significantly related to homelessness rates

across the different model specifications; that is, the relationship remains unchanged after controlling for a variety of factors.¹⁷ This result is consistent with what we heard in CoC interviews we conducted, where seven of 11 CoCs that had experienced an increase in homelessness described the cost of housing as one of the primary factors driving homelessness during the 2012 through 2018 period. However, given issues with data reliability and availability and our modelling limitations, based on the model results we cannot conclude that housing values were the primary factor—only that there is a statistically significant positive association. Specifically, in the specification that controls for all factors, a \$100 increase in rent is associated with an approximately 9 percent average increase in the homelessness rate.¹⁸ Based on the raw data, CoCs that experienced the largest increase in median rent from 2012 through 2018 also experienced a smaller decrease in the total homelessness rate than those with the smallest increase in median rent, a median annual average decrease of about 1.5 percent compared to 2.9 percent.¹⁹ The other housing variable that is statistically significantly

¹⁷Throughout the rest of the appendix we refer to a relationship being statistically significant if it is different from zero at the 90 percent confidence level or above.

¹⁸The 95 percent confidence interval for this estimate is between a 2 percent and a 16 percent increase in the homelessness rate for a \$100 increase in median rent. Note that we used median rent, which includes both those who have and have not moved recently. In places where there is rent control, median rent is likely lower for those who have not moved recently than for those looking for housing.

In alternative specifications we used the percentage of households paying more than 30 percent of the household income in rent instead of median rent and median income. Although the relationship between the percentage of households paying more than 30 percent of their income in rent and the homelessness rate was positive and significant in some specifications, it was not robust across specifications.

We also looked at rates of the unsheltered and sheltered counts separately. The relationship between median rent and rates of homelessness appears to be stronger for the unsheltered counts than for the sheltered counts.

¹⁹Those with the largest increase are defined as those in the fourth quartile of the distribution of the average annual percentage changes in median rent from 2012 through 2018. Those with the smallest increase in median rent are defined as those in the first quartile of the distribution of the average annual percentage changes in median rent from 2012 through 2018. Those with a medium level of rent increase (i.e., those in the second and third quartiles) experienced a median average decrease in the total homelessness rate of about 2 percent per year. The median of the average annual change is the median of the average year-to-year percentage change from 2012 through 2018 for CoCs in that group. For the purposes of this calculation, we determined that the median of the average annual change for each group of CoCs is a more appropriate summary statistic than the average due the presence of large year-to-year fluctuations in the homelessness rate which could drive the mean.

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related to homelessness rates is the percent of renter-occupied units. Specifically, there is a statistically significant negative relationship between the percentage of renter-occupied units and homelessness rates. This could happen if an increase in renter-occupied units is a result of an increase in the supply of housing. For example, we see that within communities, there is a statistically significant negative relationship between median rent and the percentage of renter-occupied units.

As shown in table 5, the demographic characteristics and most of the economic characteristics are not statistically significantly associated with changes in homelessness rates within communities.²⁰ The only economic variable that is statistically significantly related to rates of homelessness is the percentage of SNAP recipients; specifically, there is a positive statistically significant association between the percentage of SNAP recipients and homelessness rates, which could occur if this variable captures the vulnerable population with the greatest need better than the poverty measure.²¹

As shown in table 5, of the funding variables, the rate of Housing Inventory Count bed coverage under emergency shelter/transitional

²⁰Although some of the demographic and economic characteristics are significantly associated with rates of homelessness across CoCs, once we control for CoC fixed effects these relationships are no longer significant. For example, the percentage of the population that is veteran and the unemployment rate are positively and significantly related to rates of homelessness in a model without fixed effects, and the percentage of the population age 65 and over, the percentage of single parent households, and median earnings are negatively and significantly related to rates of homelessness, but these relationships are not significant when we control for fixed community characteristics. This result might be because these factors might not vary as much over time and are thus absorbed by the community fixed effects, which control for community-level characteristics that do not vary over time. However, if we are interested in what factors are related to changes in homelessness, the fixed-effects model is more appropriate given that it uses within-community variation and controls for all time-invariant differences between CoCs. Thus, the estimated coefficients of the fixed-effects models cannot be biased because of omitted time-invariant characteristics.

Another reason for the economic relationships not being significant in the fixed-effects model would be if the factors are highly correlated with other factors. However, we re-ran the fixed-effects model with housing characteristics, demographic characteristics, unemployment and poverty, excluding funding variables as well as all the other economic factors that were significantly correlated to poverty—such as SNAP, social security insurance, cash public assistance, and median earnings—and poverty and unemployment were still not related to homelessness rates. Note that in order to look at the correlation between poverty and each of the other economic factors, we ran fixed-effects population-weighted regressions of poverty on that economic factor.

²¹This is only suggestive evidence, given that this relationship is not robust in the sensitivity analysis below.

housing/safe haven projects is positively and statistically significantly associated with total homelessness rates. The association between bed coverage under emergency shelter/transitional housing/safe havens and homelessness rates is likely because the number of beds under these programs is mechanically related to the sheltered counts, since the sheltered counts include those in emergency shelter/transitional housing/safe havens. Therefore the association is likely because of the endogeneity due to local response. According to a CoC official, the CoC's Housing Inventory Count increased as its homelessness count increased because the local response was to expand the number of shelter and housing resources devoted to addressing homelessness.

As shown in table 5, the time-varying variables in the model account for about 34 percent of the variation in total homelessness rates within CoCs. The time-varying variables and the time invariant CoC fixed effects together account for about 98 percent of the variation in total homelessness rates within and across CoCs. However, if we are interested in how much of the year-to-year changes within CoCs the model explains, the first percentage is a more appropriate measure.

Sensitivity Analysis

Table 6 shows the results of our sensitivity analysis. We tested the sensitivity of the results to (1) excluding CoCs with more than a 50 percent change in their total homelessness rate at any point during the study period, which could indicate that they changed their methodology during the period; (2) controlling for methodological differences that could affect the count across CoCs and over time; (3) controlling for differences in weather on the day of the count that could affect the count across CoCs and over time; (4) not using population weights in regressions to check that results are not sensitive to weighting all CoCs equally; (5) using a different method for assigning counties to CoCs (i.e., including only CoCs for which all counties that overlap them do so by more than a 75 percent land overlap, excluding counties that overlap them by less than 5 percent); and (6) using 1-year ACS estimates as opposed to 5-year estimates for the housing, demographic, and economic community characteristics because, although the 1-year estimates only include areas

with populations of more than 65,000 people, they are more recent and might exhibit more variation.²²

Of the statistically significant relationships we observed in our main analysis, only the relationship between homelessness rates and median rent and the relationship between homelessness rates and bed coverage rates for emergency shelter/transitional housing/safe havens are statistically significant in all of our alternative specifications (see table 6). Of the housing characteristics, the median rent and the percentage of renter occupied units were statistically significantly related to homelessness rates in the main analysis (see table 5, column 4), but only median rent is statistically significantly related to homelessness rates in all the alternative specifications. The percentage of renter occupied units is not statistically significantly related to homelessness rates when we exclude CoCs with large changes in homelessness rates during the study

²²The regression that controls for methodology, column (2) in table 6, is for 2013 through 2018 which is the period for which methodology information is available. The methodology controls are a set of indicators for whether observation, HMIS, a client survey, a provider survey, or other methods were used for the sheltered count and whether a night-of-count, service-based, HMIS, or other method was used for the unsheltered count. Variable names or values changed in 2015 and again in 2016—for example, by allowing for a percentage for the sheltered variables instead of a “Yes” or “No” answer or further disaggregating the night-of-count variable into census, random, and known location sample types. In order to use the data for the entire 2013–2018 period, we made some assumptions. For example, we set an indicator to equal 1 if “Yes” was used for the sheltered methodologies from 2013 through 2015 or if the percentage reported from 2016 through 2018 was greater than zero. The majority of the indicators were not significantly related to the homelessness count rate (only two out of 10 were significantly related), which might be because they are not detailed enough. Note that although the methodology information available provides some high-level information on the methodology used by the CoC in a given year, it does not capture more detailed information that might affect the counts, such as the number of volunteers used.

We heard from CoCs that weather on the day of the count could affect the count; for example, CoC focus group participants told us that a snow storm on the day of the PIT count can affect the results. Thus we controlled for precipitation, snow accumulation and minimum temperature on the day of the count. Of the weather variables, only precipitation on the day of the count was negatively and significantly related to the homelessness rate. Note that given that some CoC and year observations did not have weather data—for example about 6 percent of the CoC and year observations were missing data on minimum temperature—we imputed the missing weather data with the CoC average during the period and excluded CoCs with more than 2 years of missing data.

ACS 5-year estimates cover all counties and are 5-year rolling averages. ACS 1-year estimates are current annual estimates and thus might exhibit more variation than the 5-year estimates but are only available for areas with populations of more than 65,000. Thus we took the population-weighted average county-level measures for the counties assigned to a CoC for which there were data.

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period. Of the economic characteristics, only the percentage of SNAP recipients was statistically significantly related to homelessness rates in the main analysis. However, the percentage of SNAP recipients is not statistically significantly related to homelessness rates when we exclude CoCs with large changes in homelessness rates during the study period, when we weight all CoCs equally, when we use a different method of assigning counties to CoCs, or when we use 1-year ACS estimates. Of the funding variables, the rate of bed coverage for emergency shelter/transitional housing/safe havens was statistically significantly related to homelessness rates in the main analysis and also in all of the alternative specifications.²³

Table 6: Sensitivity Analyses of Estimated of Relationships between CoC-Level Rates of Homelessness and Factors

Dependent variable: log (total homelessness rate)	(1)	(2)	(3)	(4)	(5)	(6)
Median rent (2018 dollars)	0.00076**	0.00089**	0.00083**	0.00093**	0.00087**	0.00043**
Median rent (2018 dollars) (total homelessness rate)	(0.00037)	(0.00037)	(0.00036)	(0.00036)	(0.00037)	(0.00017)
Rental vacancy rate	0.01223	0.00631	0.00617	-0.00109	0.01423	0.00293
Rental vacancy rate (total homelessness rate)	(0.01482)	(0.01152)	(0.01371)	(0.00968)	(0.01362)	(0.00458)
Renter occupied (%)	-0.03775	-0.05704***	-0.06568***	-0.05868***	-0.06556***	-0.01662***
Renter occupied (%) (total homelessness rate)	(0.02290)	(0.01766)	(0.01967)	(0.01588)	(0.02161)	(0.00572)
Black or African American (%)	0.02401	0.05734*	0.02987	0.00567	0.02780	0.01125*
Black or African American (%) (total homelessness rate)	(0.03307)	(0.03346)	(0.03555)	(0.02198)	(0.03834)	(0.00632)
Hispanic or Latino origin (%)	0.00227	0.02059	0.00410	0.03487*	0.00300	0.00724
Hispanic or Latino origin (%) (total homelessness rate)	(0.04082)	(0.02901)	(0.03315)	(0.01849)	(0.03546)	(0.02933)
Age 65+ (%)	-0.09163*	-0.02084	-0.06237	-0.01206	-0.06111	-0.01092
Age 65+ (%) (total homelessness rate)	(0.05136)	(0.05133)	(0.04825)	(0.04789)	(0.05020)	(0.01751)
Veterans (%)	-0.04830	-0.01207	-0.04478	-0.03388	-0.01170	0.00262
Veterans (%) (total homelessness rate)	(0.08146)	(0.05167)	(0.06340)	(0.03380)	(0.07694)	(0.01370)
Single-parent households (%)	-0.01649	-0.01687*	-0.01360	-0.00295	-0.00783	-0.00244

²³As noted above, this positive association is likely due to the fact that the number of beds for emergency shelter/temporary housing/safe havens is mechanically related to the sheltered counts since the sheltered counts include those in these programs. The positive association is likely due to the local response (i.e., as the number of individuals experiencing homelessness increases, localities are likely to increase the number of beds available).

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Dependent variable: log (total homelessness rate)	(1)	(2)	(3)	(4)	(5)	(6)
Single-parent households (%) (total homelessness rate)	(0.01031)	(0.00948)	(0.00962)	(0.00810)	(0.00977)	(0.00249)
Unemployment rate	-0.01964	0.00211	0.00095	0.03577	-0.01634	0.01813
Unemployment rate (total homelessness rate)	(0.03080)	(0.02700)	(0.02764)	(0.02235)	(0.02852)	(0.02027)
Supplemental Nutrition Assistance Programs recipients (%)	0.01750	0.03460***	0.02687*	0.01306	0.01006	0.01447
Supplemental Nutrition Assistance Programs recipients (%) (total homelessness rate)	(0.01433)	(0.01332)	(0.01413)	(0.01101)	(0.01503)	(0.01190)
Cash public assistance recipients (%)	-0.00571	-0.03478	-0.02465	-0.01952	-0.03624	-0.03433**
Cash public assistance recipients (%) (total homelessness rate)	(0.02699)	(0.02806)	(0.02681)	(0.02460)	(0.02865)	(0.01477)
Poverty (%)	0.01229	0.00794	0.00456	0.01269	0.02823	0.00771
Poverty (%) (total homelessness rate)	(0.02515)	(0.02269)	(0.02558)	(0.01764)	(0.02375)	(0.00627)
Social security income recipients (%)	0.02841	0.03304	0.03197	0.02504	0.03074	0.00350
Social security income recipients (%) (total homelessness rate)	(0.02654)	(0.02412)	(0.02609)	(0.02475)	(0.02942)	(0.00817)
Median earnings (2018 dollars)	-0.00002	-0.00001	-0.00002	-0.00001	-0.00003	0.00001
Median earnings (2018 dollars) (total homelessness rate)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00002)	(0.00001)
Housing Inventory Count total bed count (rapid rehousing/permanent supportive housing/other permanent housing rate)	0.00104	0.00124	0.00097	-0.00012	0.00092	0.00182
Housing Inventory Count total bed count (rapid rehousing/permanent supportive housing/other permanent housing rate) (total homelessness rate)	(0.00128)	(0.00123)	(0.00119)	(0.00113)	(0.00133)	(0.00140)
Housing Inventory Count total bed count (emergency shelter/temporary housing/safe haven rate)	0.01434***	0.01485***	0.01560***	0.01574***	0.01522***	0.01909***
Housing Inventory Count total bed count (emergency shelter/temporary housing/safe haven rate) (total homelessness rate)	(0.00244)	(0.00277)	(0.00252)	(0.00287)	(0.00266)	(0.00224)
Continuum of Care (CoC) award (2018 dollars) per capita	0.00701	0.01284	0.01529*	0.00224	0.00697	0.01570*
Continuum of Care (CoC) award (2018 dollars) per capita (total homelessness rate)	(0.00847)	(0.00866)	(0.00821)	(0.00664)	(0.00837)	(0.00874)
Total people receiving housing support rate	0.00006	0.00016	0.00036	0.00021	-0.00043	0.00050

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Dependent variable: log (total homelessness rate)	(1)	(2)	(3)	(4)	(5)	(6)
Total people receiving housing support rate (total homelessness rate)	(0.00039)	(0.00042)	(0.00040)	(0.00030)	(0.00041)	(0.00041)
Constant	4.06713*	1.78888	4.15793**	2.85734**	4.31746*	1.38793
Constant (total homelessness rate)	(2.35926)	(1.81093)	(2.08724)	(1.41557)	(2.21791)	(0.86970)
Observations	2,240	2,302	2,618	2,688	2,485	2,569
R-squared	0.36328	0.32113	0.33869	0.22503	0.31265	0.32555
Number of CoCs	320	384	374	384	355	367
CoC fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

Legend: * = significantly different from zero at 90 percent confidence level; ** = significantly different from zero at the 95 percent confidence level; *** = significantly different from zero at the 99 percent confidence level.

Source: GAO analysis of data from the U.S. Census Bureau, the Department of Housing and Urban Development, and the National Oceanic and Atmospheric Administration. | GAO-20-433

Notes: The dependent variable is the natural log of the total homelessness rate, defined as the total homelessness point-in-time count per 10,000 people. Column (1) excludes CoCs with more than a 5 percent change in their count at any point during the study period, column (2) controls for methodological differences that could affect the count across CoCs and over time for 2013 through 2018, column (3) controls for weather differences that could affect the count across CoCs and over time, column (4) presents unweighted regressions, column (5) maps counties to CoCs based on the share of land overlap and only includes CoCs where all counties have a land overlap of more than 75 percent, after excluding counties with less than a 5 percent overlap, and column (6) uses American Community Survey 1-year estimates for housing, demographic, and economic characteristics. Reported R-squared is the within R-squared. Standard errors clustered at the CoC level are in parentheses.

We also ran the model using the U.S. Census Bureau Small Area Income and Poverty Estimates instead of the poverty measure from the ACS, as well as with the unemployment rate measure from the Bureau of Labor Statistics Local Area Unemployment Statistics instead of the unemployment rate measure from the ACS, and the conclusions remained unchanged (that is, median rent was positively and statistically significantly related to the homelessness rates, and neither poverty nor unemployment were statistically significantly related). We also ran the model excluding different geographic areas, such as (1) New York City and Los Angeles, the CoCs with the largest homelessness counts, to make sure the results were not being driven by these large areas; and (2) the state of California because it was the state with the largest total homelessness count during the 2012 through 2018 period; and (3) the District of Columbia because it had the highest average rate of homelessness during the 2012 through 2018 period. The relationship between median rent and the homelessness rates remained positive and statistically significant.

Caveats

As noted above, this analysis is not meant to determine a causal link between changes in homelessness rates within communities and factors we identified. Rather, it is meant to establish whether there were statistically significant relationships between rates of homelessness and identified factors after holding other identified factors fixed, as well as after controlling for time-invariant CoC characteristics through the CoC fixed effects and for national-level shocks through the year fixed effects. As such, we interpret our model results with caution and note the following caveats:

- Even though we find a consistent positive and statistically significant relationship between median rent and rates of homelessness after controlling for a variety of factors including the CoC and year fixed effects, other factors that vary over time and that we did not control for could be related to changes in both median rent and rates of homelessness and could be driving the estimated relationship.
- There is measurement error in the homelessness counts, and thus there is measurement error in our dependent variable. If the measurement error in the dependent variable is random, it would increase the standard error, thus biasing the analysis toward not finding a statistically significant relationship. However, if the measurement error is not random and is related to our factors, it would bias the coefficients. Although we conducted sensitivity analysis by excluding CoCs with large fluctuations, controlled for methodological differences in the PIT count, and controlled for weather on the day of the count, there could be other factors related to how the count is conducted and the factors we examined—for example, if areas where rent increased happen to have improved their count at the same time by having more volunteers or by other means that we could not control for. Moreover, there is measurement error in our independent variables, given that we had to map counties to CoCs and use county level measures to calculate weighted averages at the CoC level. If the measurement error in the independent variables is random, this would bias the estimated coefficients toward zero. However, if the measurement error in the independent variables is endogenous, it could lead to upward or downward bias in the coefficients.
- Our analysis only considers a selection of factors, particularly focusing on community-level rather than individual-level factors; other factors

we did not identify in this analysis could be related to changes in rates of homelessness.²⁴ Moreover, if those factors are (1) are time varying, (2) impact the homelessness rate, and (3) are related to other explanatory factors included in the model, the coefficient on those variables could be biased.

- Given that in the fixed-effects model we are looking at changes within a community from 2012 through 2018, a factor that did not exhibit as much variation during our period of analysis might not be related to changes in rates of homelessness counts during our study period but might be related to changes in homelessness in other periods where it exhibits more variation.
- The fixed-effects model controls for all time-invariant differences between CoCs and is designed to study changes within a CoC. The estimated coefficients of the fixed-effects models cannot be biased because of omitted time-invariant characteristics but cannot be used to identify which specific time-invariant factors are related to overall levels of homelessness because all these time invariant characteristics are absorbed by the fixed effects. Thus, fixed-effects results cannot be used to specify exactly which time-invariant characteristics could explain why some communities have higher homelessness rates than others to begin with since these time-invariant characteristics are absorbed by the fixed effects.

²⁴Examples of individual-level factors not included are lack of social support, adverse health shocks, and mental illness.

Appendix III: Federal Homelessness Data from the Departments of Education and Veterans Affairs

In addition to the data collected by the Department of Housing and Urban Development (HUD), the Departments of Education (Education) and Veterans Affairs (VA) collect data on significant homeless subpopulations—youth and veterans. However, due to major differences in the definitions of homelessness used and the variance in time frames during which data were collected, we could not include Education’s data in our econometric model of factors correlated with changes in homelessness.¹ Similarly, because VA’s data are collected from only the portion of veterans experiencing homelessness who seek VA services, we could not compare them to HUD’s Point-in-Time count data or use them in our analysis. This appendix provides data quality information on Education’s Education for Homeless Children and Youth (EHCY) data and on VA’s Homeless Operations Management and Evaluation System (HOMES) data.

Department of Education

Education collects information on homeless children during the school year but does not estimate the number of children who would have experienced homelessness during breaks in the academic calendar (e.g., during the summer when school is not in session). We obtained EHCY data from school year 2013–14 through school year 2016–17 at the local education agency level without suppressed values, and for the same

¹The definition of homeless that Education uses is broader than HUD’s and comes from provisions in the McKinney-Vento Act on education of children and youth. This definition includes children and youth who are sharing the housing of other persons due to loss of housing, economic hardship, or a similar reason (that is, are doubled up); living in motels, hotels, trailer parks, or camping grounds due to the lack of alternative adequate accommodations; or living in substandard housing (McKinney-Vento Children and Youth). 42 U.S.C. § 11434a.

period at the state level without duplicated or suppressed values.² We determined that most of the EHCY program data are complete and reliable, with a few exceptions. Four states, the District of Columbia, and Puerto Rico had missing or variable results in 1 or more years. For example, there was no local education agency data for West Virginia in 2013, and there is a large number of missing observations in the unaccompanied youth counts for Wyoming from 2013 through 2016. When we asked Education about these issues, officials said some data were incorrectly loaded into the EDFacts data warehouse, which affected West Virginia's school year 2013–14 submission.³ Education's Office of Elementary and Secondary Education (OESE) said Wyoming reported all of its unaccompanied homeless youth counts as missing in school year 2014–15, but the state indicated that changes to its data collection would ensure future reporting of these data. However, the data were flagged again in school year 2015–16 for missing observations.

Seven of the 23 variables we reviewed were highly variable, including “age 3 through 5 (Not Kindergarten),” “unsheltered,” and “unaccompanied youth.” OESE officials said the smaller sizes of the student populations counted in these variables partially contribute to their variability. For the “unsheltered” and “unaccompanied youth” variables, OESE said other factors, such as the availability of shelters and affordable housing, among others, can impact these counts.

Researchers we interviewed identified homeless youth, persons experiencing unsheltered homelessness, homeless families, and homeless immigrants as particularly difficult-to-count segments of the overall homeless population. Five of the seven researchers we interviewed who have experience using EHCY data noted that one of the database's strengths is that it includes data on the doubled-up population (those living in households with more than one family).

Department of Veterans Affairs

HOMES is VA's primary platform for collecting intake, progress, and outcome information for homeless veterans as they move through VA's

²A local education agency is a term used by Education for a school district, an entity that operates local public primary and secondary schools in the United States. Education suppresses certain values for smaller school districts to protect the privacy of youth contained within its data.

³EDFacts is an Education system used to collect and analyze pre-kindergarten through grade 12 data from states on districts and schools.

system of care and synchronizing documentation across VA's homelessness programs into one platform. Data are collected and entered at the point of service, which is required within 3 days of contact with the veteran, according to VA. HOMES contains program data from eight programs in three service areas:

- **Residential treatment services.** Grant and Per Diem; Health Care for Homeless Veterans Contract Residential Services/Low Demand Safe Havens; Domiciliary Care for Homeless Veterans; and Compensated Work Therapy/Transitional Residences.⁴
- **Case management.** Housing and Urban Development–VA Supportive Housing (known as HUD–VASH) and Health Care for Homeless Veterans.
- **Justice programs.** Health Care for Re-entry Veterans and Veterans Justice Outreach.

HOMES data elements are aligned with HUD's Homeless Management Information System (HMIS) universal data elements, and there are reports in HOMES that can be uploaded to HMIS. HOMES contains data on sheltered and unsheltered homeless veterans, whereas HMIS primarily contains data on sheltered homeless veterans. In addition, given the continuous nature of data collection in HOMES, comparison with Point-in-Time count aggregated estimates are not appropriate, according to VA officials.

Because HOMES contains a record of each clinical or service encounter, each of which can contain dozens of variables, VA officials suggested that HOMES data aggregated in a VA system known as the Homeless Services Cube were appropriate for the aggregated statistics we requested. We examined HOMES records by program and year from 2012 through 2018. To assess the reliability of the data, we reviewed unique total counts by year for each program contained in HOMES for zeros, missing values, outliers, and year-over-year consistency, and we identified no significant issues.

Four of the 12 researchers we interviewed had experience using VA HOMES data, but only two considered HOMES methodology reliable for understanding changes in homelessness at the national level because

⁴Beginning in 2020, HOMES will no longer include data for the Domiciliary Care for Homeless Veterans and Compensated Work Therapy/Transitional Residences programs.

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their scope is limited to veterans who access VA services. One of the four considered HOMES methodology reliable for understanding changes in homelessness at the local level but only among VA service users.

Appendix IV: Continuums of Care Included in Focus Groups and Structured Interviews

As discussed in appendix I, we conducted focus groups and structured interviews with Continuums of Care (CoC).

We conducted focus groups with 34 CoCs including those from the following localities:

- Austin/Travis County (Texas)
- Boston (Massachusetts)
- Bristol, Bensalem/Bucks County (Pennsylvania)
- Burlington County (New Jersey)
- Cleveland/Cuyahoga County (Ohio)
- Chapel Hill/Orange County (North Carolina)
- Columbus-Muscogee/Russell County (Georgia)
- Dayton, Kettering/Montgomery County (Ohio)
- Fayetteville/Cumberland County (North Carolina)
- Glens Falls, Saratoga Springs/Saratoga, Washington, Warren, Hamilton Counties (New York)
- Hillsboro, Beaverton/Washington County (Oregon)
- Jersey City, Bayonne/Hudson County (New Jersey)
- Los Angeles (California)
- Memphis/Shelby County (Tennessee)
- Metropolitan Denver (Colorado)
- Montgomery County (Maryland)
- Morristown/Blount, Sevier, Campbell, Cocke Counties (Tennessee)
- Myrtle Beach, Sumter City & County (South Carolina)
- Napa City & County (California)
- New York (New York)

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- Northeast Oklahoma (Oklahoma)
- Oakland, Berkeley/Alameda County (California)
- Palm Bay, Melbourne/Brevard County (Florida)
- Portland, Gresham/Multnomah County (Oregon)
- Raleigh/Wake County (North Carolina)
- Riverside City & County (California)
- Salt Lake City & County (Utah)
- San Antonio/Bexar County (Texas)
- Springfield/Hampden County (Massachusetts)
- St. Charles City & County, Lincoln, Warren Counties (Missouri)
- Tehama County (California)
- Tuolumne, Amador, Calaveras, Mariposa Counties (California)
- Wilmington/Brunswick, New Hanover, Pender Counties (North Carolina)
- Worcester City & County (Massachusetts)

We conducted structured interviews with 21 CoCs including the following:

- Central Tennessee (Tennessee)
- Chico, Paradise/Butte County (California)
- Colorado Springs CoC (Colorado)
- Connecticut Balance of State CoC (Connecticut)
- Fort Pierce/St. Lucie, Indian River, Martin Counties (Florida)
- Hagerstown/Washington County (Maryland)
- Holland/Ottawa County (Michigan)
- Ithaca/Tompkins County (New York)
- Joplin/Jasper, Los Angeles City and County (California)
- Newton Counties (Missouri)
- Merced City & County CoC (California)
- New Mexico Balance of State (New Mexico)
- New York City (New York)
- Overland Park, Shawnee/Johnson County (Kansas)

**Appendix IV: Continuums of Care Included in
Focus Groups and Structured Interviews**

- Seattle/King County (Washington)
- Southern Illinois (Illinois)
- Springfield/Sangamon County CoC (Illinois)
- Tallahassee/Leon County (Florida)
- Topeka/Shawnee County CoC (Kansas)
- Troy/Rensselaer County CoC (New York)
- West Virginia Balance of State (West Virginia)

Appendix V: Homelessness Researchers Included in Structured Interviews

As discussed in appendix I, we completed 12 structured interviews with homelessness researchers. The 12 researchers we interviewed were:

- Ellen L. Bassuk, M.D.
- Daniel Brisson, Ph.D., M.S.W.
- Martha R. Burt, Ph.D.
- Thomas Byrne, Ph.D.
- Kevin Corinth, Ph.D.
- Dennis Culhane, Ph.D.
- Mary Cunningham, M.P.P.
- Christina Endres, M.S.W.
- Jill Khadduri, Ph.D.
- Stephen Metraux, Ph.D.
- Ann Elizabeth Montgomery, Ph.D.
- Matthew Morton, D.Phil., M.Sc.

As appendix I also mentions, we pre-tested our interview instrument before conducting these structured interviews. The following three homelessness researchers provided feedback on the clarity of our interview questions:

- Marybeth Shinn, Ph.D.
- Dan Treglia, Ph.D., M.P.P.
- Catherine L. Troisi, Ph.D.

Appendix VI: Comments from the Department of Housing and Urban Development



ASSISTANT SECRETARY FOR
COMMUNITY PLANNING AND DEVELOPMENT

U.S. DEPARTMENT OF HOUSING AND URBAN DEVELOPMENT
WASHINGTON, DC 20410-7000

June 18, 2020

Ms. Alicia Puente Cackley
Director
Financial Markets and Community Investment
U.S. Government Accountability Office
441 G Street, NW
Washington, DC 20548-0001

Dear Ms. Cackley:

Thank you for the opportunity to review and comment on the Government Accountability Office's (GAO) draft report titled, "Homelessness: Better HUD Oversight of Data Collection Could Improve Estimates of Homeless Population" (GAO-20-433). HUD appreciates GAO's desire to improve the quality of data on people experiencing homelessness in this country. HUD is committed to collecting accurate data to better inform solutions to end homelessness.

In the draft report, GAO affirmed that two of the three core data sets HUD uses to collect data – Point-in-Time (PIT) count, Housing Inventory Count (HIC), and Homeless Management Information System (HMIS) data – are reliable, with some limitations (pages 18 and 19 of the report). The report focused primarily on concerns with HUD's PIT count and determined that the PIT count did not provide a reliably precise estimate of the homeless population (page 2).

The report concludes that HUD's PIT count data has reliability issues and the core concerns raised were with the unsheltered aspect of the PIT count data. For instance, concerns with high fluctuations in the data (as stated on page 8) can clearly be seen in the unsheltered PIT count data, which has a median magnitude of change of 26 percent. The report raises other issues that impact the count, including the limitations of enumerators accurately identifying people experiencing homelessness (see page 6) and changes in methodologies (see page 10 through 14). These findings are concerning particularly as many areas of the country are attempting to address increases in unsheltered homelessness.

HUD appreciates the importance of understanding the accuracy of the PIT count data and is taking action to improve the count. Quality checks can be made at various levels and HUD will pursue methodologies that are effective, efficient, and cost effective. HUD agrees with Recommendation 1 that more can be done to monitor and assess the data collection methodologies CoCs are using to conduct the PIT count.

HUD agrees with Recommendation 2 and plans to strategically provide more detailed instructions on using probability sampling techniques. In providing such instructions, HUD will utilize its technical assistance (TA) resources to assist communities to the extent practicable.

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**Appendix VI: Comments from the Department
of Housing and Urban Development**

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The report acknowledges that CoCs can't keep pace with the volume of guidance HUD is providing (see page 18 of the report). HUD must consider reducing the volume of guidance and information so that the CoC program can be implemented more efficiently. Encouraging CoCs to focus on Recommendation 2 to add sampling error and bias indicators is a critical component to improve data quality and will impact HUD's ability to provide more accurate data, which impacts the funding made available to communities.

HUD will continue to dedicate resources to collect more accurate data and empower CoCs to use that data to make better-informed decisions. HUD uses its various points of influence to focus on improving the overall completeness and data quality on people experiencing homelessness. In the annual CoC Program Competition, where HUD awards over \$2 billion of funding each year, HUD has several scoring elements directly tied to submitting accurate data and analyzing that data. HUD has committed millions of dollars in technical assistance to train CoCs in how to collect and use data. HUD is creating tools to help CoCs better evaluate their data and use it to improve their homeless response system. HUD is searching for solutions to weaknesses in homeless data including data on unsheltered homelessness and data on survivors of domestic violence. All of these actions will be part of HUD's ongoing work to fulfill Recommendation 3 of the report.

One of HUD's core priorities includes using data to better understand homelessness to improve our ability to prevent and end homelessness. As such, HUD accepts the recommendations in this report and will integrate them into its effort to improve the collection and use of data regarding people experiencing homelessness and the housing and services provided to them. Thank you for conducting your analysis and for the opportunity to comment on the report.

Sincerely,



John Gibbs
Acting Assistant Secretary
for Community Planning and Development
U.S. Department of Housing and Urban Development

Text of Appendix VI: Comments from the Department of Housing and Urban Development

Page 1

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**Appendix VI: Comments from the Department
of Housing and Urban Development**

Sincerely,

John Gibbs

Acting Assistant Secretary for Community Planning and Development

U.S. Department of Housing and Urban Development

Appendix VII: GAO Contact and Staff Acknowledgments

GAO Contact

Alicia Puente Cackley, (202) 512-8678 or cackleya@gao.gov

Staff Acknowledgments

In addition to the contact named above, Paul Schmidt and Karen Tremba (Assistant Directors), Julie Trinder-Clements (Analyst in Charge), Lilia Chaidez, Janet Fong, Anne Kruse, Christy Ley, Dustin Milne, Marc Molino, Jessica Sandler, Jennifer Schwartz, Rachel Stoiko, Farrah Stone, Hannah Weigle, and Khristi Wilkins made key contributions to this report.

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