Effect of Providing Permanent Housing for the Homeless on Per Capita Homeless Rates in U.S. Cities

IDS 701 Project Final Report
Prepared by

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I. Executive Summary

The purpose of this analysis was to understand the impact on homelessness by providing permanent housing for the homeless. In the mid 2000s, after early empirical success, the United States Department of Housing and Urban Development (HUD) implemented the Housing First approach (McEvers & Pendleton, 2015). Since adoption, some cities have substantially reduced homelessness, while others have struggled. In turn, the effectiveness of this approach has been questioned. This particular analysis studied the effect from providing permanent housing (for the homeless) on per capita homeless rates between 2007 and 2021. Understanding the relationship between providing permanent housing and homeless rates could better drive investment decisions when combating homelessness.

The relationship was modeled with a linear regression including fixed and time effects, along with a number of expected confounding variables, to measure the causal relationship between permanent housing resources and homelessness; however, the results of this project suggest that there is no causal relationship between permanent housing resources and homelessness, and only found a relationship between homelessness and the confounding demographic variables (race, ethnicity, and gender).

Therefore, this analysis recommends the following approach. First, further analyze the factors causing the underlying demographic inequality across the cities with the largest homeless population, specifically with respect to healthcare, education, and income. Second, increase resources in data collection on homelessness, which includes additional measurement of homelessness in each of these cities, and collection of publicly available measurement of addiction and health data. Third, explore alternative investments in fighting homelessness beyond permanent housing in a Housing First approach, that are also targeted at reducing the underlying demographic inequality correlated with homelessness.

II. Background

The term "homelessness" was coined in the 1870s, marking the beginning of what is now known as the modern era of homelessness in the United States. However, this issue has grown increasingly complex, exacerbated by various factors such as economic recessions, the opioid epidemic, the global pandemic, the deinstitutionalization of the mentally ill, a high unemployment rate, and a shortage of affordable housing (National Academies of Sciences, Engineering, and Medicine, 2018). As a result, homelessness continues to be a pressing issue in the United States.

To address the growing homeless crisis, the Housing First concept was introduced and popularized by Sam Tsemberis and Pathways to Housing in New York during the 1990s. This approach was based on successful implementations observed in other countries. The Housing First approach provides homeless individuals and households with permanent housing first, without preconditions or barriers to entry (Canadian Observatory on Homelessness, n.d.). The goal is to provide stable housing, which enables participants in the program to address the underlying problems that led to their homelessness in the first place. A research paper by Padgett et al. provided evidence that the Housing First approach has been more effective than a Treatment First Approach.

Since its introduction, many cities have adopted the Housing First approach. While some cities, such as Columbus, Ohio and Salt Lake City, Utah, have reportedly succeeded in solving their homeless problems (Moiz, 2022), other cities have not seen similar results. As such, doubts have been raised about the effectiveness of the Housing First approach. Therefore, this project aims to answer the following question: What is the impact of providing permanent housing for the homeless on per capita homeless rates? However, since homelessness is a complex issue caused by many factors, it is critical to understand the limitations of only providing permanent housing in hopes of reducing homelessness. To account for the other factors that drive homelessness, this analysis analyzed the impact of permanent housing while accounting for several confounding variables.

According to the report "*Structural and Systemic Factors Contributing to Homelessness in Canada: An Analysis of Research Gaps and Proposed Research Directions*", there are three main groups of factors that cause homelessness: factors associated with income (i.e. unemployment, lack of education), factors associated with health (including mental health and substance abuse), and factors associated with housing (i.e., unaffordable housing, unsafe housing, and eviction) (Buckland, 2001). Furthermore, the table in *Appendix 1* of *"The 2022 Annual Homelessness Assessment Report"* (de Sousa et al., 2022) reveals that a disproportionate number of homeless individuals are Non-White and Non-Hispanic/Non-Latino, indicating that people of color are particularly vulnerable to homelessness in the United States. Therefore, racial inequality is another important factor contributing to homelessness.

To explore the relationships among these factors, this analysis utilized data from multiple sources. Due to limited public availability of homeless data, this analysis relies heavily on Point-in-Time (PIT) homeless estimates and Housing Inventory Count (HIC) data from HUD. In cases where direct datasets are unavailable, assumptions were made regarding the alignment of available data and the unquantified confounding variables. For example, it is challenging to obtain data sets directly measuring drug addiction and mental health; therefore, this analysis used mortality data as a proxy for evaluating drug addiction and mental health issues. These proxies provide the potential for misalignment in the analysis.

The aim of this analysis is to provide policymakers with a quantitative measure on the potential impact of their investment in cities experiencing substantial homelessness. Therefore, this analysis focused on cities where homelessness was a significant problem at the start of the Housing First Implementation. In 2007, New York and Los Angeles had the largest homeless populations, each with over 45,000 homeless individuals. Detroit and Houston also had over 10,000 homeless individuals, and 15 other cities had over 5,000 homeless individuals (*see Appendix 2*). These 19 cities were the focus of this analysis.

Ideally, this analysis would be completed with an experiment, randomly assigning each city with a random amount of permanent housing per capita to analyze the impact of investing in permanent housing for the homeless on homelessness. However, this ideal experiment is not feasible due to the significant investment required. Instead, this project analyzed per capita homeless rates using a linear regression to infer the relationship between permanent housing and homelessness, while accounting for poverty, unemployment, drug addiction, mental health, and racial equity levels. While permanent housing capacity is not the primary driver of homelessness, it is expected to be the variable which public policy has the most control over. Additionally, permanent housing alone cannot necessarily help people with mental health and substance abuse issues; however, as mentioned, there is evidence that suggests a Housing First approach is more successful at helping with these issues than a Treatment First approach. (Padgett et al., 2011)

III. Analysis Design

Data Sources

The data used for this analysis was: estimates of homelessness, permanent housing inventory for the homeless, population and demographic estimates, poverty estimates, unemployment estimates, drug overdose deaths, and suicide deaths for each city of interest. According to HUD, homeless data is primarily collected by entities known as Continuum of Care (CoC) programs.

The CoC program is a coalition of institutions and organizations that provide funding to local communities to develop housing and services for people experiencing homelessness. Each CoC program can vary in size based on the local population and is responsible for specific regions, which do not necessarily map to specific counties or cities. *(U.S. Department of Housing and Urban Development, 2021)*. The dataset used in this analysis was aggregated and mapped onto CoCs, which can span multiple counties *(see Appendix 2).* However, since this analysis focused on the 19 CoCs with the largest amount of homelessness (as of 2007), these CoCs were relatively easily mapped to the largest cities. All the data was aggregated and merged based on CoC per year, for years ranging from 2007 to 2021.

The specific datasets collected and aggregated were:

1. **Point-in-Time (PIT) Homeless Estimates from 2007 to 2022 by CoC**

   The point-in-time (PIT) estimates of homelessness were obtained from HUD (U.S. Department of Housing and Urban Development., 2023). This data was used to represent the amount of homelessness in a given city. The dataset provides information on homelessness for each CoC operating region in a given year, with each spreadsheet tab representing data for a year between 2007 to 2022. This data was combined into the overall homeless count for each year.

2. **Housing-Inventory-Count (HIC) from 2007 to 2022 by CoC**

   The Housing-Inventory-Count (HIC) data was obtained from HUD (U.S. Department of Housing and Urban Development., 2023). This data was used to represent the amount of housing resources provided to the homeless in each city. The dataset provides information on the number of different types of housing provided for the homeless, including both temporary and permanent housing units for each CoC operating region in a given year, with each spreadsheet tab representing data for a year between 2007 and 2022.

3. **Small Area Income and Poverty Estimates (SAIPE) from 2007-2021 by County**

   The Small Area Income and Poverty Estimates (SAIPE) utilized in this project was sourced from the United States Census Bureau. This data was used to represent the amount of low income people in a city. The dataset includes comprehensive information on the annual poverty estimates of counties throughout the United States. The Census Bureau calculates these estimates using a home-brewed statistical model, which combines summary data from American Community Survey (ACS), federal income tax returns, SNAP benefits, decennial census, postcensal population estimates, Supplemental Security Income recipiency, and economic data from the Bureau of Economic Analysis (BEA).

4. **Local Area Unemployment Statistics (LAUS) from 2007-2021 by County**

   The annual unemployment rates for counties across the United States comes from the United States Bureau of Labor (Rice & Galbraith, 2008). This data was used to represent the amount of people who cannot find work in a city. The LAUS data is derived using the industry-standard Handbook method.

5. **Mortality Multiple Cause Data from 2007-2021 by County**

   The mortality data used in this study was obtained from the Centers for Disease Control and Prevention (CDC) Wonder online databases, which provide information on various causes of death, including drug overdose and suicide/self-harm deaths, collected from death certificates of U.S. residents (Centers for Disease Control and Prevention, n.d.) and encoded using the 10th revision of International Classification of Diseases (ICD) Codes. The drug overdose data and the suicide death data were used to represent the level of addiction and mental health issues in a city. The drug overdose deaths are identified using codes X40–X44, X60–X64, X85, and Y10–Y14, while the suicide deaths are identified using codes *U03, X60–X84, and Y87.0.

6. **Population Data from 2007-2021 by County**

   Population and demographic composition estimates were obtained from the United States Census Bureau. This data was used to represent the demographic inequality within a city.

Data Quality Concerns Associated with the Publicly Available Data

While the point in time homeless count provides a data point representing the prevalence of homelessness in a given area, it is important to note that the count is conducted only once a year, on the coldest night in January, by a group of staff members and volunteers. Furthermore, due to limited resources, some Continuums of Care (CoCs) may need to estimate the total number of homeless individuals based on a street count and then scale up the data proportionally using census population data or sampling. This approach may vary across different CoCs and can be problematic since the coldest day of the year may impact cold climates differently from warm climates. Despite these challenges with data collection methods, the CoCs operation is expected to be consistent, and provide reasonably reliable data on the relative levels of homelessness in their geographic area. While there may be differences in estimates across regions, the PIT homeless count provides the best publicly available estimates of homelessness. Furthermore, fixed effects analysis is expected to account for any consistent over or under representation of the data.

As previously mentioned, drug-related deaths were used as a proxy for levels of addiction within a city, and suicide-related deaths were used as a proxy for mental health and general health issues that could lead to homelessness within a city. The expectation in this analysis is that the correlation between this data and homelessness is equivalent to the correlation between the underlying confounding variables associated with addiction and health, and homelessness. Nevertheless, misalignment between these correlations could over, or under, represent the relationship between these underlying factors and homelessness. Furthermore, if these relationships are not accurately represented, the coefficients of the other variables in the regression will be over or under represented accordingly.

Additionally, drug-related death data for Douglas and Broomfield counties in Colorado were missing. In the case of Douglas County, the dataset does not include 2008 data. To fill this void, the data was imputed by averaging the number of deaths per year between 2007 and 2009. Also, the drug-related death data for Broomfield County only includes 7 of the 15 years. These missing values were imputed with zeros. Similarly, the Broomfield County suicide data is missing 5 years of information, and these missing values were also imputed with zeros.

Trends in Homelessness since Housing First Implementation

1. **Percentage Change in Homelessness between 2007 and 2021**

   The two bar charts below show per capita homelessness in each city (*Figure 1*), and how it has changed from 2007 to 2021 (*Figure 2*). The chart on the left shows per capita homelessness in 2007, while the chart on the right shows the percent change from 2007 to 2021. Many cities were able to substantially reduce their homelessness, but some have not reduced it nearly as much, and New York's per capita homelessness has grown. In 2007, Detroit had the highest per capita homelessness, followed closely by the District of Columbia. Detroit, in particular, successfully reduced their per capita homelessness by 92%, whereas the District of Columbia only reduced theirs by 16%. Furthermore, New York's per capita homelessness has increased by 33%. Overall, approximately half of the 19 CoCs were able to reduce homelessness by more than 50%, while the other half were not (*see Appendix 3 for CoCs*).

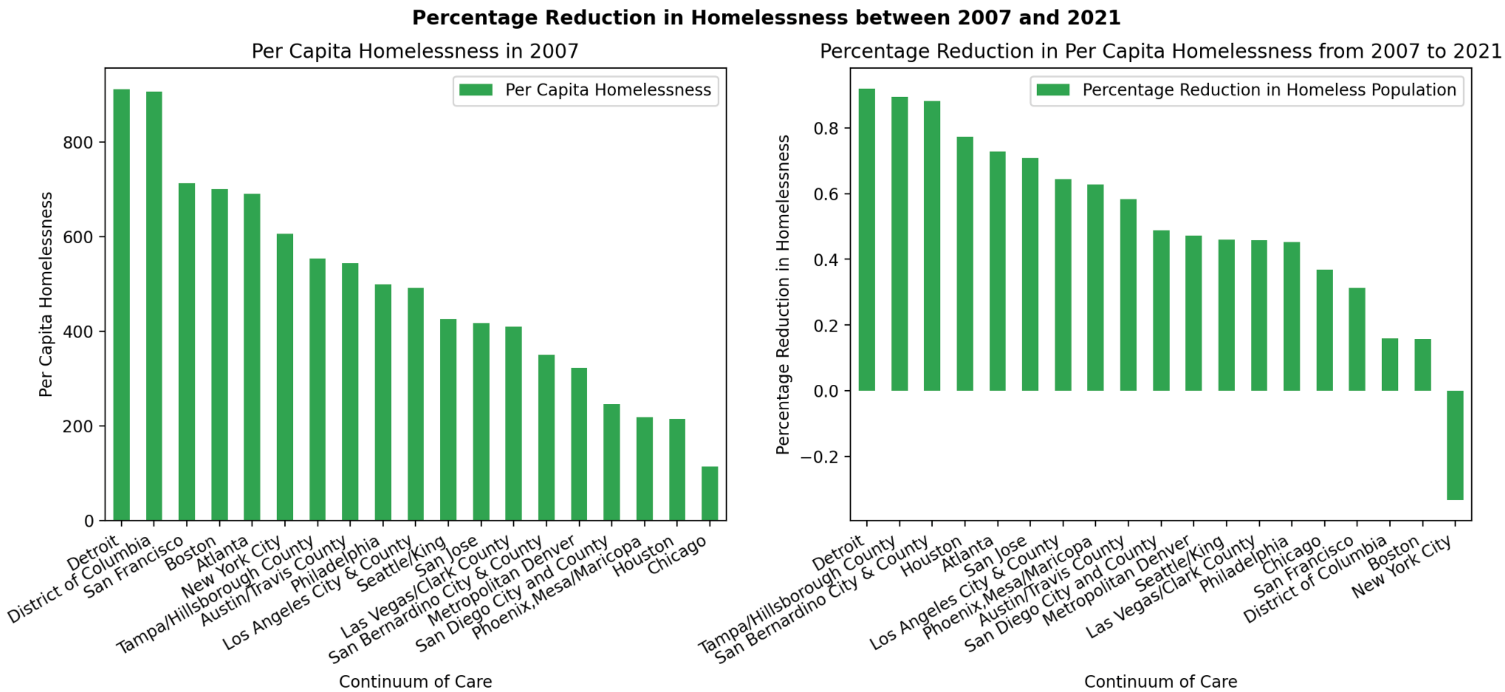

Figure 1. Per Capita Homelessness in 2007

Figure 2. Percent Change in Per Capita Homelessness between 2007 and 2021

2. Comparison of Success Against January Temperatures

As mentioned in the data concerns section, homeless estimates are only measured once a year, on what is expected to be the coldest day of the year. While CoCs are expected to be able to account for this through consistency (i.e., each CoC is only measuring its own region and should be able to account for its own challenges in collecting proper estimates), the above charts show an apparent trend that the colder climate cities have had less success in reducing homelessness than the warmer climate cities.

Building on this, the below scatter plot shows the city's percentage change in homelessness versus its average January temperatures. The scatter plot does appear to show an apparent trend, where, aside from Detroit, nearly all of the cities with a reduction in homelessness less than 50% have average January temperatures below 45 degrees Fahrenheit. Having colder winters should certainly affect the approach in how cities handle infrastructure for their homeless population, but it should not be an underlying cause for having a large homeless population.

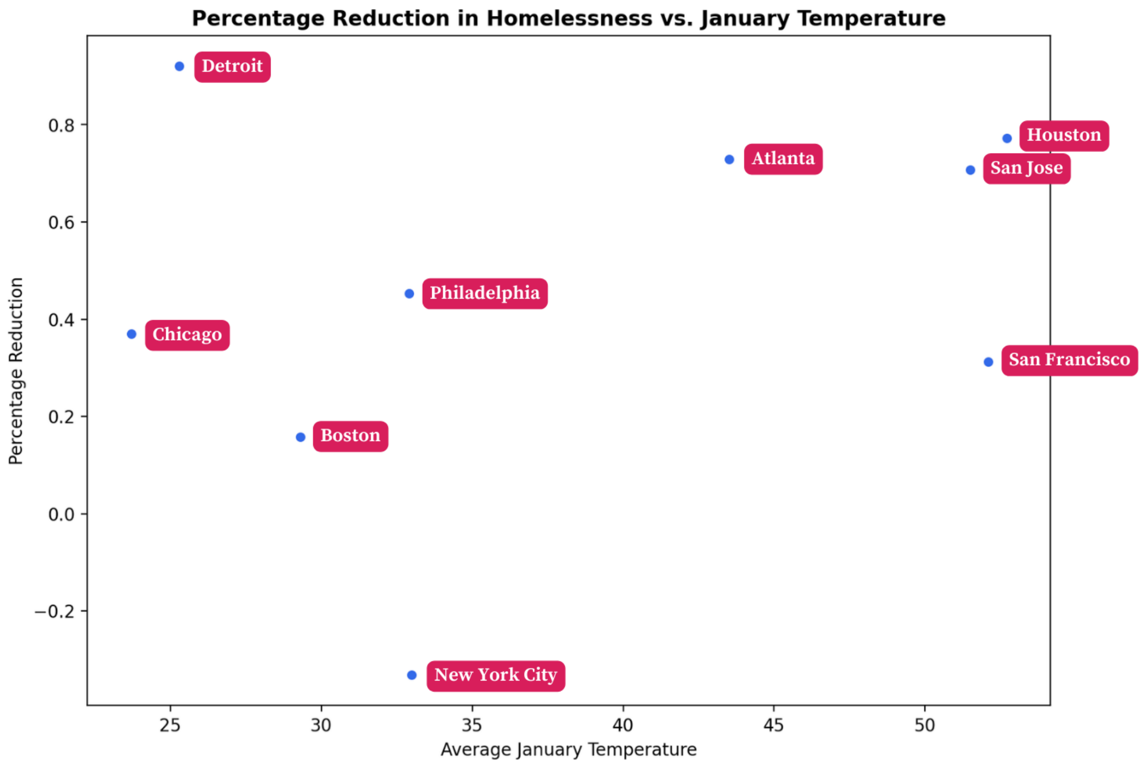

Figure 3. Percentage Change in Per Capita Homelessness against Temperature in January

3. Permanent Housing provided by CoCs following Housing First Implementation

As seen in the below graph, there is a dramatic difference in the amount of permanent housing provided by the CoCs who reduced homelessness by more than 50%, and those who did not. However, counterintuitively, the CoCs which provided the most permanent housing per capita are not the CoCs that have reduced homelessness by more than 50%. The graph below illustrates the permanent housing resources provided for the homeless over the years 2007 to 2021.

Generally, there was a steady increase in permanent housing resources provided by CoCs within each group; however, the increase was much greater for the CoCs who have not substantially reduced homelessness. Because homelessness is a complex issue, this graph should be interpreted as the CoCs who have not been able to substantially reduce homelessness need to continue providing more permanent housing for the homeless than those who have substantially reduced homelessness.

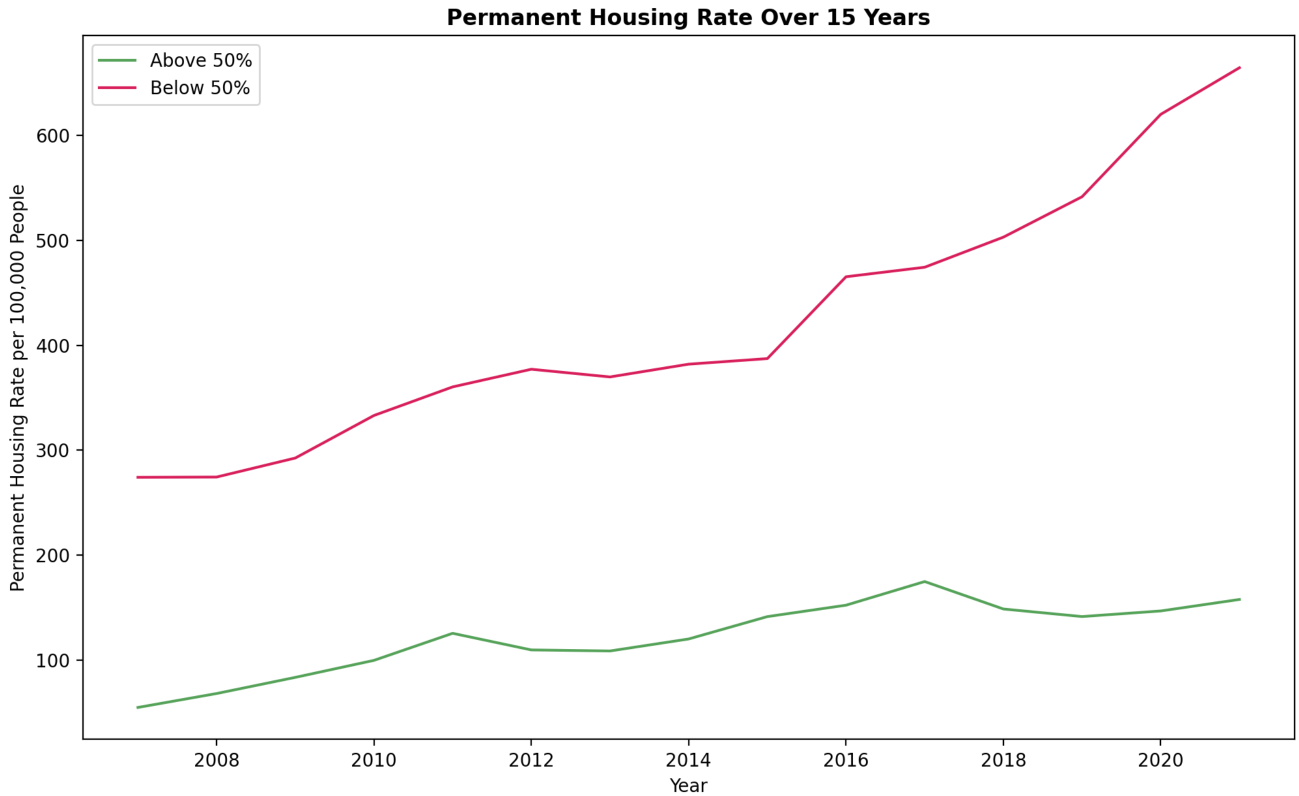

Figure 4. Per Capita Permanent Housing for the Homeless from 2007 to 2021

4. Trends in Associated Underlying Factors

The below graphs show how the expected underlying factors (rates of unemployment, poverty, suicide, and drug overdose) have changed over time within the cities who substantially reduced homelessness, compared to the cities whose homelessness was reduced by less than 50%. While there is no clear divergence in the trends between the cities who substantially reduced homelessness and the cities who did not, the graphs do show that the unemployment rates and drug overdoses managed to stay substantially lower in the cities with substantially reduced homelessness. Surprisingly, poverty rates and suicide rates were generally higher in cities that were able to reduce their homelessness by more than 50%.

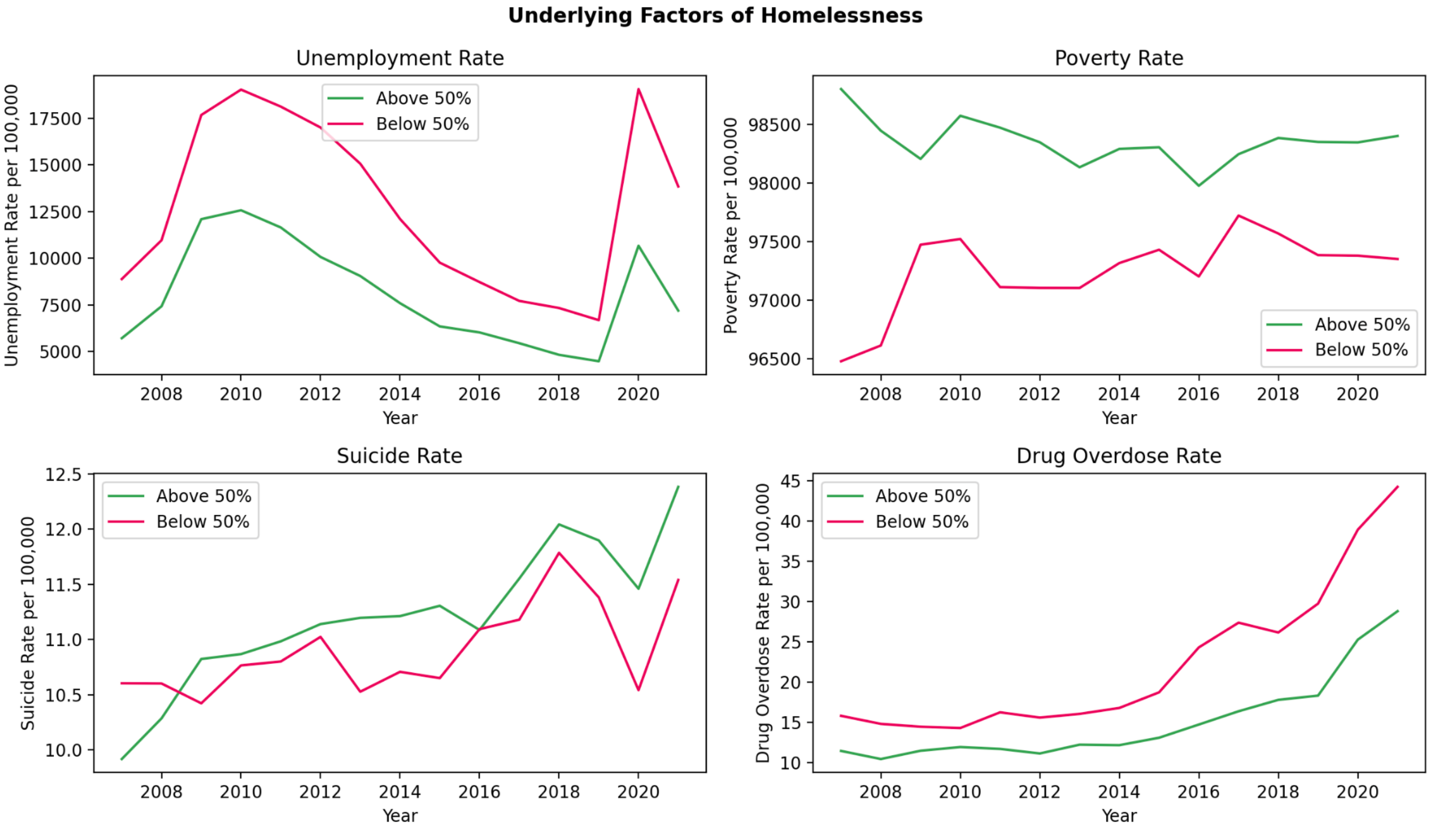

Figure 5. Contributing Factors of Homelessness Compared Across CoCs that Reduced Homeless by atleast 50%

5. Demographics Across Cities who Substantially Reduced Homelessness

The below graphs show how racial demographics have changed in the cities which have substantially reduced homelessness compared to the cities which have not. Similar to the previous set of graphs, there is no clear divergence in trends between the two groups of cities, but in general, the cities with the greatest reduction in homelessness tend to have a lower per capita population of minorities. This suggests that the ability to reduce homelessness could be tied to some of the intrinsic racial inequalities and systemic bias within a city.

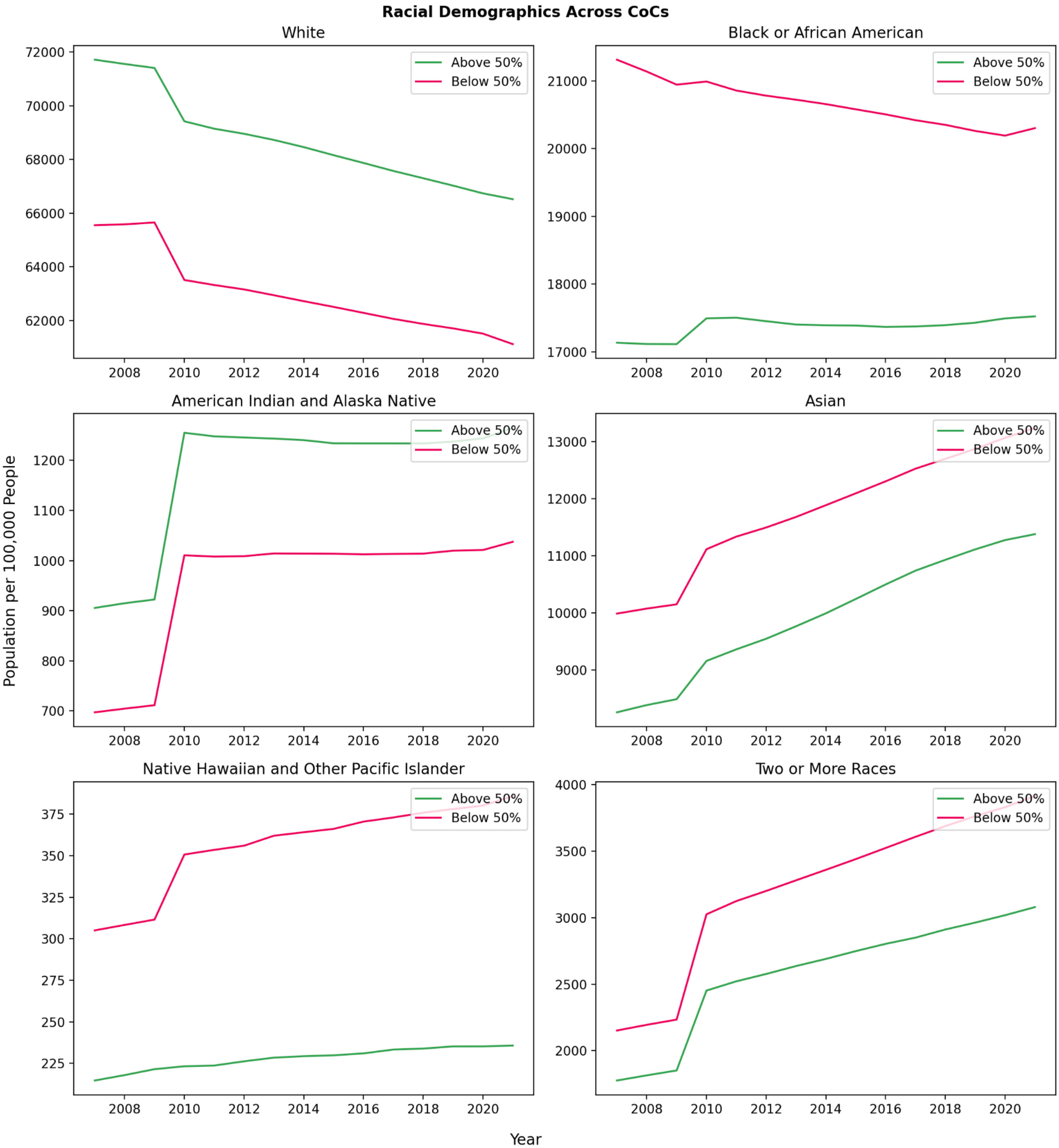

Figure 6. Trends in Demographics of Cities who substantially reduced homelessness compared to cities that did not

Methodology of Analysis

While the above graphs show general trends in homelessness and its related factors since the Housing First implementation, to understand the causal relationship between permanent housing and homelessness, this analysis focused on a least squares regression with fixed and time effects over the period between 2007 and 2021 in the 19 metropolitan areas. This regression controlled for poverty, drug addiction, health, and racial equity levels using the publicly available data. While the fixed effects control for unobserved heterogeneity across the CoCs, and the time effects control for unobserved time variance over the course of the analysis. Once the regression was completed, it was confirmed appropriate by analyzing it against its assumptions. For reference, *Appendix 4* checks for these assumptions.

IV. Results

According to this model, there is no expected effect on homelessness when increasing permanent housing per capita. Furthermore, demographics were shown to be the only statistically significant factors impacting homelessness, which suggests demographic dynamics of a city may underlie reasons for homelessness. But more surprisingly, this therefore suggests, economics, drug use, and mental health have no bearing on homelessness in cities, which seems unlikely (*See Appendix 5 for table of linear coefficients*).

Interpretation and Limitation

Homelessness is a complex issue, with no one solution for every person; however, in homeless studies common factors include mental health, addiction, and disability. Therefore, it is unexpected for the model to show that these factors are not statistically significant, while demographics are. There are two likely explanations for these findings. First, the mortality data is more misaligned from its underlying factors than expected (i.e., deaths from drug overdose do not accurately represent the level of addiction in a city). Second, the underlying causes of homelessness (addiction, mental illness, lack of education, unemployment, etc.) are highly correlated with the demographic inequalities in a city (more correlated than the mortality data). Therefore, to accurately understand homelessness on the aggregate, a model needs data that can accurately represent the underlying causes of demographic (race, ethnicity, and gender) inequality in each CoC, especially with respect to healthcare (particularly addiction and mental health), education, and income.

Furthermore, as discussed, homeless data is only measured once a year, in January, and the warmer cities appear to have had greater success in reducing homelessness than the colder cities. While this could be due to different housing needs, collecting homeless data once per year, particularly by volunteers on the coldest night of the year, seems to lead to the potential for poor estimation. CoCs should implement more regular measurement to ensure more consistent and accurate data.

V. Conclusion

The goal of this project was to identify resources that a CoC can provide to reduce homelessness, and more specifically, identify the causal relationship between CoC provided permanent housing and homelessness. Unfortunately, this analysis found no causal relationship between permanent housing and homelessness, and instead found relationships between demographics and homelessness.

Therefore, this analysis recommends the following approach. First, further analyze the factors causing the underlying demographic inequality across these CoCs (specifically with respect to health care, education, and income). Second, increase resources in data collection on homelessness, which includes additional measurement of homelessness in each CoC and collection of publicly available measurement of addiction and health data. Third, explore alternative investments in fighting homelessness beyond permanent housing in a Housing First approach, that are also targeted at reducing the underlying demographic inequality correlated with homelessness.

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Appendix

Appendix 1: Homelessness rates by Race from "The 2022 Annual Homelessness Assessment Report" (de Sousa et al., 2022)

	All People		Sheltered People		Unsheltered People	
	#	%	#	%	#	%
All People	582,462	100%	348,630	100%	233,832	100%
Age						
Under 18	98,244	16.8%	87,960	25.2%	10,284	4.2%
18 to 24	40,177	6.9%	26,981	7.7%	13,196	5.6%
Over 24	444,041	76.3%	233,689	67.0%	210,352	90.1%
Gender						
Female	222,970	38.3%	152,693	43.8%	70,277	30.0%
Male	352,836	60.6%	193,366	55.5%	159,470	68.3%
Transgender	3,588	0.6%	1,593	0.5%	1,995	0.9%
A Gender that is not Singularly 'Female' or 'Male'	2,481	0.4%	846	0.2%	1,635	0.7%
Questioning	609	0.1%	132	0.0%	477	0.2%
Ethnicity						
Non-Hispanic/Non-Latin(a)(o)(x)	442,220	75.9%	269,964	77.4%	172,256	73.5%
Hispanic/Latin(a)(o)(x)	140,230	24.1%	78,666	22.6%	61,564	26.5%
Race						
American Indian, Alaska Native, or Indigenous	19,618	3.4%	8,843	2.5%	10,775	4.6%
Asian or Asian American	8,261	1.4%	3,909	1.1%	4,352	1.9%
Black, African American, or African	217,366	37.3%	154,557	44.3%	62,809	26.9%
Native Hawaiian or Pacific Islander	10,461	1.8%	4,692	1.3%	5,769	2.5%
White	291,395	50.0%	157,637	45.2%	133,758	57.2%
Multiple Races	35,383	6.1%	18,992	5.4%	16,391	7.0%

Appendix 2: Manual Mapping of Cities in Project and Their Corresponding FIPS Codes

	CoCs	FIPS
1	NY-600 (New York City CoC)	36005 (Bronx County) 36047 (Kings County) 36061 (New York County) 36081 (Queens County) 36085 (Richmond County)

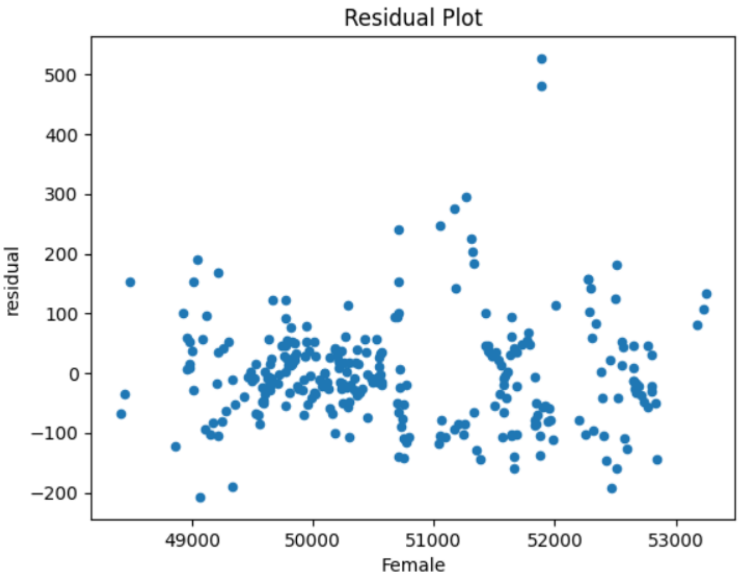
2	CA-600 (Los Angeles City & County CoC)	06037 (Los Angeles County) - LA CoC excludes the cities of Glendale, Pasadena and Long Beach
3	MI-501 (Detroit CoC)	26163 (Wayne County)
4	TX-700 (Houston, Pasadena, Conroe/Harris, Ft. Bend, Montgomery, Counties CoC)	48201 (Harris County) 48339 (Montgomery County) 48157 (Fort Bend County)
5	CO-503 (Metropolitan Denver CoC)	08001 (Adams County) 08005 (Arapahoe County) 08013 (Boulder County) 08014 (Broomfield County) 08031 (Denver County) 08035 (Douglas County) 08059 (Jefferson County)
6	AZ-502 (Phoenix, Mesa/Maricopa County CoC)	04013 (Maricopa County)
7	WA-500 (Seattle/King County CoC)	53033 (King County)
8	PA-500 (Philadelphia CoC)	42101 (Philadelphia County)
9	NV-500 (Las Vegas/Clark County CoC)	32003 (Clark County)
10	CA-601 (San Diego City and County CoC)	06073 (San Diego County)
11	CA-500 (San Jose/Santa Clara City & County CoC)	06085 (San Diego County)
12	CA-609 (San Bernardino City & County CoC)	06071 (San Bernardino County)
13	GA-500 (Atlanta CoC)	13121 (Fulton County)
14	FL-501 (Tampa/Hillsborough County CoC)	12057 (Hillsborough County)

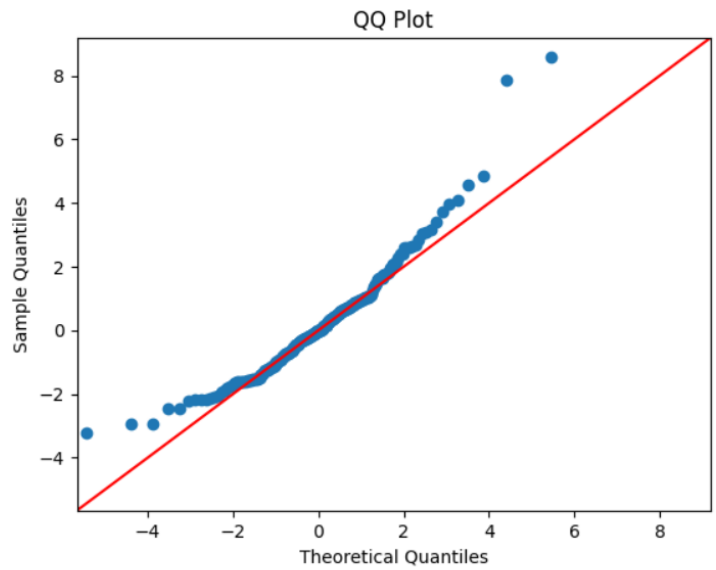
15	IL-510 (Chicago CoC)	17031 (Cook County)
16	CA-501 (San Francisco CoC)	06075 (San Francisco County)
17	DC-500 (District of Columbia CoC)	11001 (District of Columbia)
18	TX-503 (Austin/Travis County CoC)	48453 (Travis County)
19	MA-500 (Boston CoC)	25025 (Suffolk County)

Appendix 3: CoCs that Managed to Reduce Homelessness by atleast 50% and Less Than 50% between 2007 and 2021

Reduced Homelessness by at least 50%		Reduced Homelessness by less than 50%	
AZ-502	Phoenix,Mesa/Maricopa	CA-501	San Francisco
CA-500	San Jose/Santa Clara City & County	CA-601	San Diego City and County
CA-600	Los Angeles City & County	CO-503	Metropolitan Denver
CA-609	San Bernardino City & County	DC-500	District of Columbia
FL-609	Tampa/Hillsborough County	IL-510	Chicago
GA-500	Atlanta	MA-500	Boston
MI-501	Detroit	NV-500	Las Vegas/Clark County
TX-503	Austin/Travis County	NY-600	New York City
TX-700	Houston, Pasadena, Conroe/Harris, Ft. Bend, Montgomery	PA-500	Philadelphia
		WA-500	Seattle/King

Appendix 4: Residual and QQ Plots of Linear Regression for checking assumptions





Appendix 5: Table of Linear Regression Results

Variable	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Intercept	7293.2	2936.6	2.4835	0.0137	1508.3	1.308e+04
Female	-0.1575	0.0414	-3.8034	0.0002	-0.2390	-0.0759
Hispanic	-0.0197	0.0097	-2.0291	0.0436	-0.0388	-0.0006
Population	0.0001	6.165e-05	1.7182	0.0871	-1.552e-05	0.0002
African American	-0.0106	0.0113	-0.9417	0.3473	-0.0328	0.0116
American Indian/Alaskan Native	0.3597	0.0795	4.5255	0.0000	0.2031	0.5162

Asian	0.0158	0.0146	1.0827	0.2800	-0.0129	0.0444
Drug Deaths Rate	-0.6121	1.4759	-0.4147	0.6787	-3.5196	2.2954
Multiple Races	0.1114	0.0492	2.2618	0.0246	0.0144	0.2084
Pacific Islander	0.0784	0.2471	0.3174	0.7512	-0.4083	0.5652
Permanent Housing Rate	-0.0020	0.0762	-0.0258	0.9795	-0.1520	0.1481
Poverty Rate	0.0061	0.0120	0.5075	0.6123	-0.0176	0.0298
Suicide Deaths Rate	-2.0725	6.7828	-0.3056	0.7602	-15.434	11.289
Unemployment Rate	0.0008	0.0016	0.4633	0.6436	-0.0025	0.0040

* Includes Fixed Effects and Time Effects, with clustered covariances.