# Impact of the Distribution of Funding for Homelessness Relief Programs on Racial Demographics

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ABSTRACT

Homelessness has emerged as a multifaceted crisis affecting individuals and families globally. In recent years, there has been a significant rise in the number of individuals experiencing homelessness, leading to increased attention from policymakers and the public alike. In response to the escalating homelessness crisis, governments have established CoC programs as a central approach through means such as sustained support, transitional housing, and permanent housing. In this paper, we will conduct an analysis of funding allocation in the Continuum of Care (CoC) programs and its implications for homelessness across diverse racial categories. This study seeks to unravel the differential impact of these factors on racial communities through data analysis. Preliminary findings indicate that while funding mechanisms are crucial, their effects on homelessness are not uniform across racial groups. This investigation underscores the need for targeted, racially informed strategies in addressing homelessness, offering valuable insights into policymaking and intervention efforts.

## Introduction

The escalating crisis of homelessness has become a complex and urgent concern, affecting individuals and families worldwide. Overall, homelessness has seen a steady decline with an uptick from the COVID-19 pandemic (PIT and HIC Data Since 2007). The demographic distributions of homelessness populations have been disproportionately leaned towards Black populations and men (O'flaherty, B. 2018). Governments have responded by implementing various strategies to address this issue, with the Continuum of Care (CoC) programs being implemented in the United States. The Continuum of Care (CoC) homelessness relief programs are structured as a coordinated network of local organizations and agencies working together to address homelessness in a specific geographic area. These programs are overseen by the U.S. Department of Housing and Urban Development (HUD). Funding distribution is typically based on a competitive application process, where local organizations and service providers apply for grants from HUD, and the allocation is determined based on the merits and alignment with CoC's strategic priorities and goals. CoC programs offer sustained support, transitional housing, and permanent housing solutions. Despite their widespread adoption, the effectiveness of specific CoC program types and the distribution of funds in reducing homelessness is a question worth exploring. In light of the existing literature, this study aims to further explore the effectiveness of various CoC programs by analyzing the allocation of funds and their impact on homelessness levels across different states in the United States. By employing a regression model, and accounting for extraneous variables, we seek to better understand the relationship between CoC program funding and point-in-time homelessness estimates as well as impacts on specific demographics on a state level. The overarching goal of this research is to examine how funding distribution in CoCs, as well as other political and socioeconomic factors, influences homelessness across different racial demographics. By examining the distribution of funds and their regional effects on homelessness levels, we aim to provide valuable insights that can inform policymakers' decisions and lead to more targeted and effective strategies for addressing homelessness nationwide.

## Literature Review

In Corinth (2017) he uses panel data from the AHAR for 2007-2014, state-year fixed effects, and CoC fixed effects, and time-varying CoC controls to look within CoC variation over time and its correlation with the point-in-time homelessness estimations. He finds that for each 100 permanent supportive housing beds, this correlates with a decrease of point-in-time homelessness by roughly 10, with a greater weight on individuals. This paper is relevant to the research to the question that we are trying to answer as it uses a similar analysis of teaching the impacts of CoCs and its impact on point-in-time homelessness measurements. On an aggregate level, only three policies of subsidized apartment placements, prevention, and permanent supportive housing have demonstrated a positive impact. In the case of prevention, providing modest assistance to individuals at risk of homelessness can prevent many from becoming homeless seems to be effective. Factors that most influence aggregate homelessness are weather, labor market conditions, housing prices, and possibly policies, but minor changes in unemployment or rents surprisingly do not cause significant shifts in homelessness (O'flaherty, B. 2018). As of the current literature as of 2018, the only three policies that seem to affect homelessness are placements into subsidized apartments, prevention, and permanent supportive housing, with the limitation of the first two factors being only studied in the context of New York City (O'flaherty, B. 2018). The positive impact of COCs is evident, but the distribution of funds and their impact on aggregate homelessness levels by region is what we aim to study. Existing literature on homelessness reveals insight into the base structures of homelessness relief, but does not deeply analyze the racial disparities within homelessness relief. Quigley and Raphael (2001) explored the economic determinants of homelessness in North America which found that housing market dynamics, income distribution, and institutional factors play pivotal roles. However, while their research was comprehensive, it didn't delve deeply into the racial disparities in homelessness. Culhane et al. (1994) highlighted the racial and ethnic differences in the use of emergency shelters among homeless adults in which they found that Black individuals are overrepresented in shelters compared to their overall population. Such studies underscore the importance of exploring the racial dimension of homelessness but often don't investigate the funding aspects in depth.

## Data

Data regarding award amounts and distribution CoC's CoC Award Summary Reports by Component and Project Type dataset from the HUD (US Department of Housing and Urban Development) and the Point-in-Time Estimates from the HUD. Data regarding state characteristics including poverty rate, unemployment rate, and political affiliation were taken from the University of Kentucky Center for Poverty Research (UKCPR) National Welfare Data, 1980-2021. Data regarding state population demographic breakdown by race was used from the Census State Population by Characteristics datasets for our relevant years. The data for CoC funding amount distribution was limited to the years 2018-2021, limiting the scope of our data. The funding amounts by state were normalized to the percent of that award amount by state. For the purpose of testing, the District of Columbia was omitted as a state due to incomplete data from the HUD and UKCPR datasets. We normalized overall homelessness counts to ensure a consistent interpretation across states, by scaling values between 0 and 1.

## Empirical Strategy

### Overview

Using the CoC Award Summary Reports by Component and Project Type dataset from the HUD (US Department of Housing and Urban Development) and the Point-in-Time Estimates from the HUD, we will use a regression model to see if there is a relationship between the distribution of funds towards certain programs and the homelessness population estimates. We will conduct an analysis on a state level, controlling for variables such as unemployment rate,

poverty rate, and political affiliation. Before we create our final model, we will create data visualizations to better build a foundational understanding of the independent and dependent variables to better instruct the construction of our model. First, generating a stacked bar chart not only gives a holistic view of the racial makeup of the homeless population but also highlights disparities.
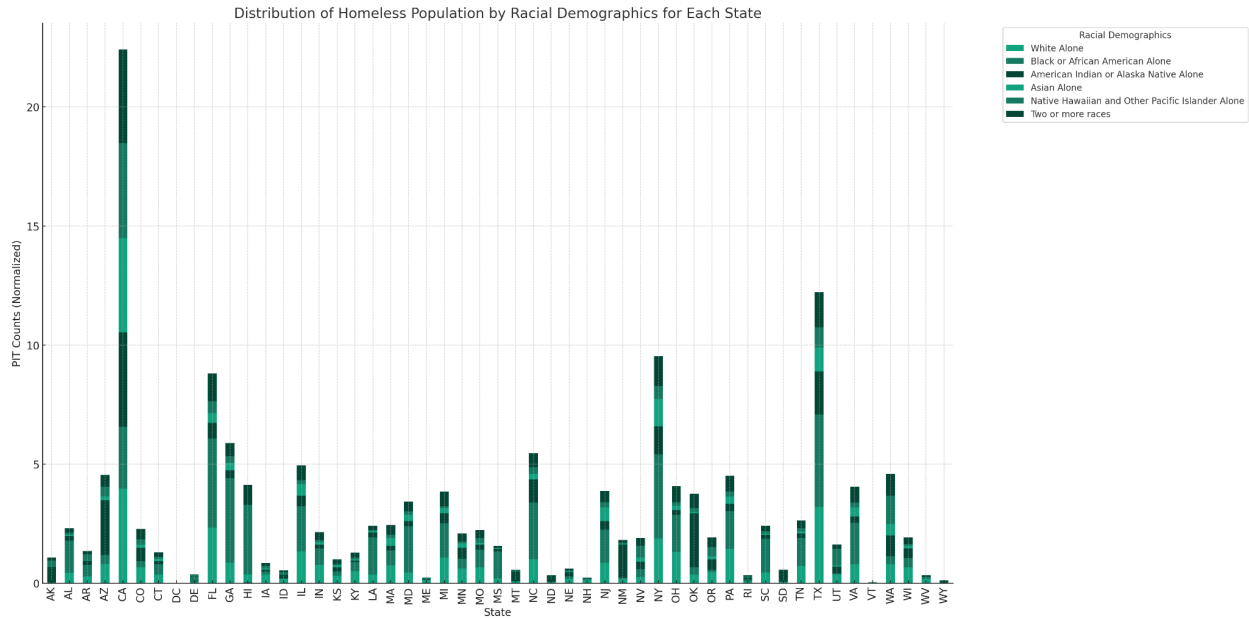


**Figure 1.** Distribution of Homeless Population by Racial Demographics for Each State

We can see that Washington (WA) State presents a diverse homeless demographic with notable counts across several racial categories. The state reports high numbers of white homeless individuals (18,516), followed by notable counts for those identifying with multiple races (4,012), and substantial counts for Asian, American Indian or Alaska Native, and Native Hawaiian or Other Pacific Islander demographics. This diversity could be attributed to the state's overall demographic makeup, migration trends, or unique challenges faced by these racial communities. Particularly, the elevated numbers for the American Indian or Alaska Native group may point to longstanding systemic or historical challenges this community encounters. On the other hand, Louisiana (LA) presents a different racial composition concerning its homeless population. While there's a considerable count of white homeless individuals, the state predominantly showcases Black or African American homeless individuals. This trend could reflect Louisiana's overall demographic distribution, given its rich African American cultural and historical roots. Yet, the pronounced representation of Black or African American homeless individuals also spotlights potential socio-economic challenges and systemic issues they might be disproportionately encountering. This variance in racial breakdown in homelessness populations by state underscores the need to balance the baseline differences by race in the final model. In order to balance this, we can utilize data from the US Census to create variables for the overall racial percentages by state to control for baseline population disparities by state and to reduce potential confounding variables. Next, we can plot the relationships between different award percentages against overall homelessness counts.
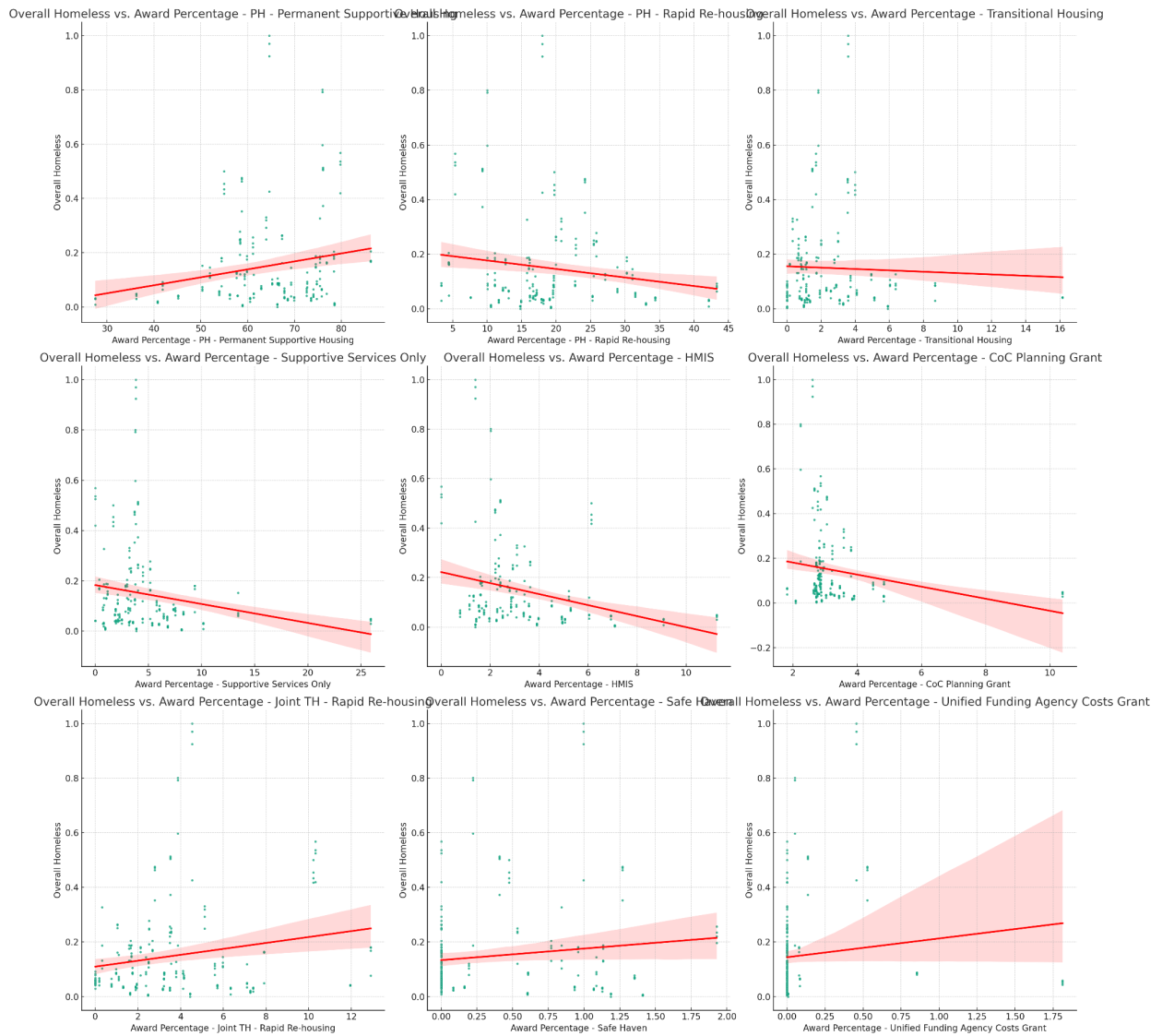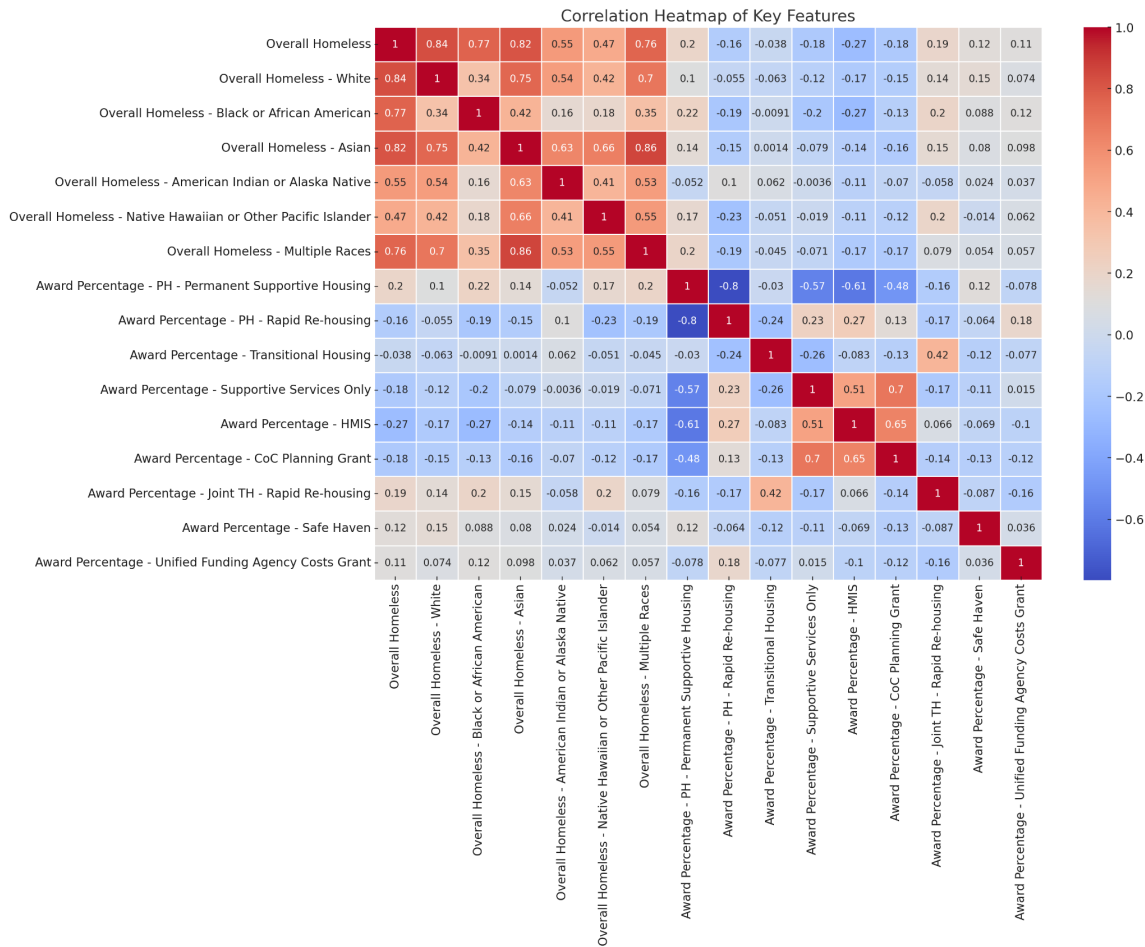
**Figure 2.** Overall Homelessness vs. Award Percentages

## Scatterplots with Regression Lines

These scatter plots illustrate the relationships between overall homelessness counts and percentages of CoC Program Funds awarded to different types of programs. The red line represents the regression line, giving a best-fit linear representation of the relationship with the opaque red area representing a 95% confidence interval for the regression estimate.

## Visible trends for each category:

- **Supportive Services**: There seems to be a positive correlation between the percentage of CoC Program Funds awarded to Supportive Services Only and the overall homelessness counts. As the percentage of funding for this service increases, the overall homeless counts also tend to increase.
- **Transitional Housing**: A slight negative correlation can be observed. This suggests that an increase in the percentage of funds allocated to Transitional Housing might be associated with a decrease in overall homelessness counts.
- **Permanent Supportive Housing**: The relationship seems to be more scattered, making it harder to discern a clear trend.
- **Joint TH - Rapid Re-housing**: There's a slight positive correlation. This suggests that as the percentage of funding allocated to these projects increases, the overall homeless counts may also increase.
- **HMIS (Non-Dedicated):** The correlation appears to be slightly positive.
- **CoC Planning Grant**: The relationship looks neutral, with no clear upward or downward trend.
- **Safe Haven**: The relationship is scattered but leans towards a positive correlation.
- **Unified Funding Agency Costs Grant**: There's a weak positive correlation observed.
- **HMIS (Dedicated):** The correlation appears neutral.



**Figure 3.** Correlation Heatmap of Overall Homelessness Counts and Award Percentages

Next, we can look at a Correlation Heatmap of Overall Homelessness Counts and Award Percentages to see potential relationships for each specific race group. The overall trends seen from this visualization can give us a preliminary understanding of the relationships between award amounts and overall homelessness counts. From this heatmap, we can see that there are strong positive correlations among different racial demographic counts of homelessness, which is expected because states with higher overall homeless counts would likely have higher counts across racial demographics. "Overall Homeless - Black or African American" seems to have a moderate positive correlation with the "Percentage of CoC Program Funds Awarded to Supportive Services Only" and the "Percentage of CoC Program Funds Awarded to Joint TH - Rapid Re-housing Projects", which suggests that as the percentage of funds allocated to these two services increases, the count of Black or African American homeless individuals may also increase. Next, "Overall Homeless - White" shows a slight negative correlation with the "Percentage of CoC Program Funds Awarded to Transitional Housing", which may indicate that an increase in funding for Transitional Housing could be associated with a decrease in the number of homeless White individuals. Additionally, most racial demographics seem to have a positive correlation with the "Percentage of CoC Program Funds Awarded to Supportive Services Only". This requires further investigation to understand the potential impact of such services on different racial groups. Interestingly, there's a negative correlation between "Overall Homeless - Asian" and the "Percentage of CoC Program Funds Awarded to Permanent Supportive Housing". This suggests that as the allocation to Permanent Supportive Housing increases, the Asian homeless count might decrease. However, it is important to note that we cannot extrapolate causation from this correlation visualization. Analyzing this heatmap allows us to make a more informed selection of variables and interactions to be tested in the final model.

## Lagged Model

Testing a lagged model is relevant to the case of homelessness because we must consider the lag between when funding decisions are made and when their effects become apparent on the ground. However, this method does lead to the omission of one year's data, as the prior year's data serves as a predictor for the subsequent year. Before running the final model, we will run the lagged model shown below with State and Year fixed effects to see if this yields any valuable insights.

$$Homelessness\ Counts_{i,t} = \beta_0 + \beta_1 \times Lagged\ Homelessness\ Count_{i,t-1} + \beta_2 \times State_i + \beta_3 \times Year_t + \epsilon_{i,t}$$

- $Homelessness\ Counts_{it}$ the count of homeless individuals for a specific racial demographic in state $i$ during year $t$.
- $Lagged\ Homelessness\ Counts_{it-1}$ is the count of homeless individuals for that racial demographic in state $i$ during the previous year ($t$-1)
- $State_i$ represents the fixed effects for each state.
- $Year_t$ captures the fixed effects for each year.
- $\epsilon_{it}$ is the error term

## Results of the initial lagged model

Overall Homeless - White:
- $R^2 = 0.942$
- Lagged Coef: -0.0298 (This means for a unit increase in the previous year's White homelessness, the current year sees a decrease of 0.0298 units. This negative relationship is counterintuitive and suggests potential other factors in play.)

Overall Homeless - Black or African American:
- $R^2 = 0.931$
- Lagged Coef: 0.0181 (For a unit increase in the previous year's Black or African American homelessness, the current year sees an increase of 0.0181 units, suggesting continuity in the trend.)

Overall Homeless - Asian:
- $R^2 = 0.897$
- Lagged Coef: 0.0059 (For a unit increase in the previous year's Asian homelessness, the current year sees an increase of 0.0059 units, suggesting continuity in the trend.)

Overall Homeless - American Indian or Alaska Native:
- $R^2 = 0.874$
- Lagged Coef: 0.0208 (For a unit increase in the previous year's American Indian or Alaska Native homelessness, the current year sees an increase of 0.0208 units, suggesting continuity in the trend.)

Overall Homeless - Native Hawaiian or Other Pacific Islander:
- $R^2 = 0.901$
- Lagged Coef: 0.0021 (For a unit increase in the previous year's Native Hawaiian or Other Pacific Islander homelessness, the current year sees an increase of 0.0021 units, suggesting continuity in the trend.)

Overall Homeless - Multiple Races:
- $R^2 = 0.883$
- Lagged Coef: 0.0211 (For a unit increase in the previous year's homelessness for those identifying with multiple races, the current year sees an increase of 0.0211 units, suggesting continuity in the trend.)

The $R^2$ values for each demographic are relatively high, ranging from 0.874 to 0.942 suggesting that our independent variables (lagged homelessness, state, and year) collectively explain a significant proportion of the variance in the dependent variable for each racial demographic. For most demographics, there's a positive correlation between the lagged homelessness variable and the current year's homelessness. This means that if the number of homeless individuals for a specific racial group increased in the previous year, it's likely to increase this year as well. This trend suggests a persistence in the homelessness numbers across years.

## Final Regression Model

The final regression model combines multiple linear regression, state and year fixed effects, and a lagged approach to analyze the relationships between homelessness counts and various predictors. By utilizing fixed effects, we control for inherent state characteristics and overarching yearly trends. The equation for the final model is shown below:

$$Homelessness\ Counts(specific\ demographic)_{i,t} = \beta_0 + \beta_1 \times Lagged\ Homelessness\ Count_{i,t-1}$$
$$+\beta_2 \times HMIS\ Percentage_{i,t-1}\ \beta_3$$
$$\times Supportive\ Services\ Only\ Percentage_i + \ldots + \beta_k Control\ Variables_{i,t}$$
$$State_i \times Year_t + \epsilon_{i,t}$$

- $Homelessness\ Counts_{it}$ the count of homeless individuals for a specific racial demographic in state $i$ during year $t$.
- $Lagged\ Homelessness\ Counts_{it-1}$ is the count of homeless individuals for that racial demographic in state $i$ during the previous year ($t$-1)
- $State_i$ represents the fixed effects for each state.
- $Year_t$ captures the fixed effects for each year.
- $\epsilon_{it}$ is the error term

Control Variables Used:

- State Minimum Wage
- Governor is Democrat (1=Yes)
- Democratic Senator Count
- Republican Senator Count
- Democratic House Count
- Republican House Count
- HMIS Percentage
- Permanent Housing Percentage
- Rapid Re-Housing Percentage
- Supportive Services Only Percentage
- Transitional Housing Percentage
- Other Percentage
- Homelessness Prevention Percentage

# Results

| Demographic | Award Type | Correlation with Homelessness | Change per +1% Increase in Funding |
|---|---|---|---|
| White | Permanent Supportive Housing | Positive | 8.53 |
| | Joint TH - Rapid Re-housing | Positive | 86.15 |
| | Transitional Housing | Negative | -49.97 |
| | HMIS | Negative | -78.37 |
| Black or African American | CoC Planning Grant | Positive | 293.18 |
| | Joint TH - Rapid Re-housing | Positive | 126.57 |
| | Unified Funding Agency Costs Grant | Positive | 681.85 |
| | Transitional Housing | Negative | -73.58 |
| | HMIS | Negative | -186.22 |
| Asian | Permanent Supportive Housing | Positive | 0.49 |
| | Joint TH - Rapid Re-housing | Positive | 4.37 |
| American Indian or Alaska Native | PH - Rapid Re-housing | Positive | 4.48 |
| Native Hawaiian or Other Pacific Islander | Permanent Supportive Housing | Positive | 0.87 |
| | Joint TH - Rapid Re-housing | Positive | 8.22 |
| | PH - Rapid Re-housing | Negative | -1.65 |
| | Transitional Housing | Negative | -5.43 |
| Multiple Races | Permanent Supportive Housing | Positive | 3.93 |
| | Joint TH - Rapid Re-housing | Positive | 15.9 |

## Notable trends for each race group:

**White**: HMIS Percentage: There seems to be a slight positive correlation between the HMIS award percentage and the homeless count for White individuals. As the percentage of funding to HMIS projects increases, there might be a

corresponding increase in the White homeless count. Supportive Services Only Percentage: There's a noticeable negative correlation. As the funding for supportive services goes up, the White homeless count might decrease. Other award percentages show more scattered patterns, suggesting weaker correlations.

**Black or African American**: HMIS Percentage: A similar pattern to the White demographic is observed, suggesting that HMIS funding might influence both these groups similarly. Supportive Services Only Percentage: The negative correlation is less pronounced than in the White demographic but still present.

**Asian**: The plots are more scattered, indicating weaker correlations between award percentages and homeless counts. However, there's a slight negative correlation with the Supportive Services Only Percentage.

**American Indian or Alaska Native**: HMIS Percentage: A positive correlation is evident, similar to the White and Black or African American demographics. Supportive Services Only Percentage: There's a discernible negative correlation, suggesting that more funding in this area might be associated with a decrease in homelessness for this group.

**Native Hawaiian or Other Pacific Islander**: The plots are highly scattered, suggesting weaker correlations. However, the HMIS Percentage and Supportive Services Only Percentage show similar patterns as other racial groups.

**Multiple Races**: Patterns are somewhat consistent with the previously discussed groups. The HMIS Percentage shows a positive correlation, while the Supportive Services Only Percentage displays a negative correlation.

## Discussion

The overarching question aimed to understand the influence of these factors on the disparities in homelessness experiences across racial lines. Our results may add to the existing literature by exploring the different impacts on racial groups, a dimension less explored in prior research. Increasing funding for HMIS projects might be associated with a rise in homelessness counts for most racial groups, particularly White, Black or African American, and American Indian or Alaska Native. More funding in this area might correlate with a decrease in homelessness for most racial groups, with the effect most pronounced for the White demographic. Some possible explanations for a negative lagged coefficient for the White homeless population could be that as homelessness rates increase, this would cause more aggressive intervention measures the following year, leading to a reduction in numbers. It is important to note that the interpretation of these findings should be taken with caution, and while the model explains a significant proportion of the variance, there could be external factors not included in the model that also play a crucial role in determining homelessness rates for different racial demographics.

Some limitations present were that we were limited to only four years of analysis, 2018-2021, due to dataset limitations for distribution of award amounts. Additionally, there is an inherent challenge of underreporting inconsistencies in the nationwide data collection processes which may not account for hidden groups. Although the strength of the differences between race groups may not be fully representative given dataset limitations, the presence of a difference in how funding different types of programs impacts races serves is an interesting topic worth expanding upon in future research. Future studies may delve deeper into understanding the specific systemic issues faced by individual racial groups, the efficacy of different types of CoC programs, or the long-term impacts of policy and funding distribution shifts. Practitioners and policymakers should approach the homelessness challenge with a nuanced lens, recognizing the differential impacts on racial demographics. Our findings suggest that while increasing funding is crucial, its allocation strategy is another aspect to consider.

# Conclusion

We aim to analyze the relationship between CoC program funding allocations and racial disparities in homelessness. Our findings highlight that while certain award types, such as Permanent Supportive Housing and Joint TH - Rapid Re-housing, are universally linked to increases in homelessness counts across racial lines, the nuanced impact of other funding areas like HMIS and Supportive Services Only varies depending on the racial demographic in question. For instance, while the White homeless population showed a potential decrease with more funding for supportive services, the relationship for other racial groups was not as pronounced. This suggests that a one-size-fits-all approach to addressing homelessness may not be effective. As regions grapple with the overarching goal of reducing homelessness, acknowledging and addressing these racial disparities is not just a matter of equity but is central to devising effective, sustainable solutions.

However, the results are not without limitations. The correlations observed, though indicative of patterns, do not necessarily imply causation. Moreover, there could be external factors not accounted for in our study that play pivotal roles in influencing homelessness rates. To further substantiate our findings and conclusions, additional research that incorporates a wider range of variables as well as longitude would be beneficial for yielding more insight to the question of funding distribution on racial demographics of homelessness populations.

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