QUANTITATIVE EVALUATION OF INTERVENTIONS TO COMBAT CHRONIC HOMELESSNESS: SHORT-TERM VS. LONG-TERM SERVICES

A Thesis submitted to the Faculty of the Graduate School of Arts and Sciences of Georgetown University in partial fulfillment of the requirements for the degree of Master in Public Policy in Public Policy

By

Shiri Yadlin, B.A.

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Shiri Yadlin, B.A.

Thesis Advisor: Andrew Wise, Ph.D.

ABSTRACT

Over the past decade a new type of intervention to combat chronic homelessness has emerged to supplement the traditional emergency shelter model: long-term care that places individuals and families experiencing homelessness directly into permanent housing instead of transitional, time-limited shelter. In this paper, I use Point-in-Time Census and Housing Inventory Count data from HUD to investigate the effectiveness of these interventions in eliminating chronic homelessness. I estimate both Fixed Effects and Pooled OLS models to examine the relationship between use of long-term interventions and counts of chronically homeless individuals nationwide. These models indicate that a higher share of total services allocated to long-term interventions is associated with a lower count of chronic homelessness, after controlling for grant funding and demographic characteristics. Specifically, a ten-percentage point increase in share of total beds allocated for long-term interventions correlates with a twenty-person reduction in chronic homelessness. No other variables are significant predictors of chronic homeless counts, suggesting that the most important tool for eliminating chronic homelessness is not funds or community characteristics, but rather service type. Therefore, I advocate for increased use of long-term interventions, such as Permanent Supportive Housing and Rapid Re-Housing, to best eradicate chronic homelessness in the United States.
The research and writing of this thesis is dedicated to all who helped along the way: my family, who kindly read these endless pages without any idea what I was rambling about; my friends who endured both my whining and nerdy excitement with patience and grace; my professors who nobly ensured I understood the purpose of a p-value; my advisor who provided constant encouragement and validation while repeatedly reminding me that there is no penalty for finishing early; and of course my Team 3 people, who continue to motivate me to use my voice and everything else within my power to fight for an end to homelessness.

Many thanks,
Shiri Yadlin
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INTRODUCTION

The purpose of this study is to evaluate common types of interventions used to combat homelessness. I use Point-in-Time Census and Housing Inventory Count data to investigate the effectiveness of various programs in battling chronic homelessness across the United States. Categorizing interventions into two broad categories—time-limited and non-time-limited—I seek to understand which are more successful in providing lasting relief from homelessness. My hypothesis is that “long-term” interventions such as Permanent Supportive Housing are more effective at combating chronic homelessness than “short-term” interventions such as emergency and transitional services.

On a single night in January 2016, there were 549,928 people experiencing homelessness; 77,000 of whom were chronically homeless. A variety of services and policies seek to reduce that number, but some are more effective than others at permanently transitioning people out of homelessness. Traditionally, efforts to fight homelessness have been exclusively siloed, emergency-based responses where individual entities provide immediate, specific, and time-limited services. Over the past ten years, however, there has been a rise in collaborative provision of low-barrier, holistic, non-time-limited services in addition to the traditional model. In these newer, long-term interventions, individuals and families are placed directly in permanent housing using either vouchers or public subsidies, to immediately alleviate the condition of homelessness, skipping over emergency or transitional shelter altogether. These long-term interventions are designed to offer stability and break the cycle in and out of homelessness that plagues the chronically homeless population. While individuals may transition in and out of

\[a\] The 2016 Annual Homelessness Assessment Report (AHAR) to Congress (2016).
homelessness at various points in their lifetimes, those who are chronically homeless have
experienced homelessness for more than a year or more than four times in the past three years.\(^b\)
New long-term interventions focus primarily on this population.

Each year, HUD collects national data on services available to the homeless population
and counts the number of people experiencing homelessness across the country, but there is little
national-level analysis comparing different jurisdictions’ interventions, and little quantitative
evidence supporting the effectiveness of permanent interventions over emergency ones. Though
anecdotal evidence exists, this paper and analysis will attempt to investigate whether the
quantitative data match this evidence.

The unit of analysis in this study is 407 Continuum of Care (CoC) areas in the United
States.\(^c\) CoCs refer to both geographic areas and collaborative partnership entities. They are set
up by a coalition of non-profits, government agencies, and other similar bodies within a
geographic area that work together to address homelessness in their regions.\(^d\) In some cases, a
CoC consists of a single city, in some cases a county, and in other cases a combination of the
two. Each CoC receives its own grant funding, provides its own services, and conducts its own
annual census of people experiencing homelessness within its borders. Every state has at least
one CoC. Example maps of CoCs in two states are provided in the Background and Literature
Review section of this paper.

I use two sets of HUD data in this analysis. The Point-in-Time census (PIT) supplies

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\(^b\) Homeless Emergency Assistance and Rapid Transition to Housing: Defining ‘‘Chronically
\(^c\) There were 407 CoCs in 2016, the most recent year of data available for this study. CoCs
expand and collapse slightly each year. A list of how many CoCs were studied in each year is
provided in the Data section of this paper.
\(^d\) Introductory Guide to Continuum of Care (CoC) Program (2012).
numbers of homeless individuals and families in each CoC, divided into descriptive categories. These categories include chronically homeless, homeless children, homeless individuals, homeless families, and others. The key dependent variable in this study is total number of chronically homeless individuals in each CoC, found in the PIT data. More information on the methodology behind the PIT census is found in the Data section of this paper.

The Housing Inventory Count (HIC) provides data on the number of available beds for homeless interventions in each CoC, as reported by the authorities in each CoC. The categories include emergency shelter beds, transitional housing units and beds, permanent supportive housing units, and rapid re-housing units, among others. The key independent variable in this study is the number of permanent and Rapid Re-housing units as a percentage of total beds or units available: a category I call “long-term interventions.” These interventions contrast “short-term interventions,” made up of emergency and transitional shelter—more traditional forms of anti-homelessness services.

My hypothesis is that those areas with a higher percentage of beds allocated to long-term services will have fewer chronically homeless individuals than those areas that focus on emergency services. In other words, a higher share of long-term beds will lead to lower counts of chronic homelessness. Because I suspect potential time-invariant CoC-specific characteristics to

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*While it may seem obvious that long-term interventions reduce homeless counts, because someone in permanent housing will not be counted in a homeless census the following year, the use of total *chronically* homeless as the dependent variable in this study addresses this problem by measuring change in rates of homelessness for people who are homeless long-term rather than those in and out of shelter. This study focuses on long-term homelessness, measuring if these interventions provide lasting effects for the people experiencing homelessness. Furthermore the use of the lagged version of the key independent variable allows me to measure whether these long-term interventions effectively keep people out of homelessness in future years. By capturing the relationship between long-term services and chronic homelessness, I measure the*
affect the relationship between share of long-term beds and total numbers of chronically homeless individuals, I use both multivariate pooled Ordinary Least Squares and Fixed Effects models to estimate this relationship across all CoCs in the years 2007 to 2016. Because there could be a lagged effect of services on the count of chronically homeless in the next year, I also estimate a pooled OLS and FE model using a version of the key independent variable lagged one year. The key controls in this study include the amount of grant funding provided to the CoC and demographic and economic characteristics of the CoC.

The results of these robust regressions indicate that there is a statistically significant negative relationship between share of beds devoted to long-term services and total count of chronically homeless individuals. Both pooled OLS and FE models using both the same-year and lagged version of the long-term beds variable produced significant regressions, with F-statistics significant at the 99 percent level, providing substantial evidence to claim that non-time-limited services are more effective at combating chronic homelessness than short-term interventions.

This paper begins with a review of literature on interventions to end homelessness, assessing what research currently exists in this space and identifying gaps in the analysis. I then build theoretical and empirical models for the analysis and introduce the data, including both the sources and my manipulations. I describe characteristics of key variables and address potential problems in the data, and finally, discuss results with a sensitivity analysis included. I end with an exploration of policy implications and suggestions for further research, based upon my results.

effectiveness of these interventions in providing lasting relief from chronic homelessness: effectively ending the condition of homelessness rather than providing temporary shelter.
BACKGROUND AND LITERATURE REVIEW

History of Homelessness Services and Legislation in the United States

In 1984 the U.S. Department of Housing and Urban Development (HUD) published its first nation-wide profile of homelessness (Brush, Gultekin, & Grim, 2016). Though homelessness certainly existed in the United States prior to this publication, the national analysis helped shed light upon both the seriousness of the problem and the lack of resources to address it. In the decades since, a series of federal programs have attempted to address this issue and a variety of theories regarding the most effective type of assistance have emerged (Moulton, 2013). Figure 1 shows the trends in levels of homelessness and chronic homelessness nationwide over the past decade.

Figure 1: Levels of Total Homeless and Total Chronically Homeless. (Source: PIT Counts 2007-2016)
The McKinney-Vento Homelessness Assistance Act of 1987,f the first federal legislative effort to combat homelessness, initiated a series of fifteen programs designed to aid people experiencing homelessness by meeting a variety of needs, including employment, emergency shelter, transitional and permanent housing, and healthcare (Moulton, 2013). However, due to concerns about lack of coordination and related inefficiencies in these siloed efforts to combat homelessness, HUD implemented the Continuum of Care (CoC) program in 1995. The goal of this program was to create a more collaborative approach to serving the homeless.g

These efforts continue today. The CoC program is designed to bring related organizations and agencies together, including both public and non-profit sector organizations, to serve the homeless population of a given geographic area. The CoC, both a geographic area and an entity in and of itself, presents one application to HUD for funding each year, and is responsible for disseminating that funding to appropriate agencies as well as coordinating homeless services and prevention activities in that geographic region. Beginning in 2007, CoCs were charged with conducting an annual count of sheltered homeless individuals in their communities (the PIT Count), and a biennial count of unsheltered populations (Garrett 2010). Figures 2 and 3 show maps of CoC boundaries within California and New Jersey, as two examples of how CoCs are arranged. As seen in these maps, the entire state is covered by non-overlapping CoCs and the breakdown of CoCs within each state varies.

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g Introductory Guide to the Continuum of Care (CoC) Program (2012).
Figure 2: Continuums of Care in New Jersey. (Source: HUD Exchange)

Figure 3: Continuums of Care in California. (Source: HUD Exchange)
In 2009, the Homelessness Emergency Assistance and Rapid Transition to Housing Act (HEARTH Act)\(^h\) reauthorized McKinney-Vento with some changes. In addition to consolidating competitive grant programs and increasing emphasis on homelessness prevention, the HEARTH ACT also introduced a new rural housing stability program and clarified the definitions of chronic homelessness. These changes demonstrate increased commitment to combating homelessness on both national and local levels, and renewed commitment to seeking solutions for this population.

Though HUD has shown increased efforts to quantify and understand the homeless population across the country, there remains concern about accuracy and reliability of data within this field. Brush, Gultekin, and Grim (2016) lament the current methodology’s potential bias in counting homeless families in particular, fearing systematic undercounting and resulting neglect when basing service provision on these false numbers. Similarly, though data collection itself has increased and standardized substantially since the introduction of the annual PIT census, little national-level analysis has been done using this data. To this date there has also been a lack of research evaluating the effectiveness of interventions to address homelessness. Previous studies have focused on specific populations, such as the mentally ill or veterans, or included broader analyses of homeless programs without distinguishing between long- and short-term interventions as in my analysis. Research has been done on the cost-effectiveness of services to the homeless and on certain interventions within certain populations, though, and an overview of these relevant research points follows.

Cost Effectiveness of Homeless Services

Several studies in the past decade have attempted to assess the cost-effectiveness of services to the homeless. A comprehensive cost-benefit analysis of three government-based homeless programs in Western Australia revealed favorable outcomes for clients, measured by the programs meeting their goals (Flatau et al., 2008). This unique analysis, which used quantitative data and qualitative surveys of both consumers and providers, focused on programs designed to house people experiencing homelessness, to provide rental assistance to struggling families to prevent homelessness, and to support the transition of individuals re-entering their communities after time in jail or prison. These are three streams of anti-homelessness work covered by many homeless assistance programs in the United States as well. Each program was found to meet its goals: those without shelter gained shelter, those fleeing domestic violence found increased safety and stability, and those at risk of losing their homes were able to keep them. Qualitative analysis of quality of life, as reported by consumers, also improved (Flatau et al., 2008).

Flatau et al. concluded that these services led to significant savings in government expenditures, namely long-term projected costs the government would have paid had these individuals remained or become homeless. Because a majority of the clients of the services also suffered chronic health problems and had been tied to the criminal justice system, the costs expended on the services were mild in relation to the potential costs that would have been incurred in the health and criminal justice areas. Researchers projected even more robust savings as the strategy of the interventions improved (Flatau et al., 2008).

Though conclusive, this study was limited in its timeline and impact as it did not
distinguish between permanently housed and temporarily housed individuals, and emphasized
cost-effectiveness in terms of savings rather than holistic long-term impacts on consumers
themselves.

Another more recent cost analysis, focused on federal homelessness assistance in the
United States, reached similar conclusions about the cost-effectiveness of services to the
homeless (Moulton, 2013). Moulton’s key question was whether housing assistance reduced
chronic homelessness, and he used a fixed effects model to investigate the impact of new federal
funding for services to the homeless on levels of chronic homelessness. Drawing upon data from
both ACS and PIT Counts, Moulton estimated two models, one to predict the effect of new
homeless funding in period \( t-1 \) on the rate of chronic homelessness in period \( t \), at the CoC level,
including community fixed effects, and another that eliminated community fixed effects to
include rate of homelessness in time \( t-1 \) as an additional explanatory variable. Both models
produced similar results: that spending to assist people experiencing homelessness can reduce
chronic homelessness. Specifically, Moulton concluded “a $1 per capita increase in federal
homeless funding is associated with a 1.80 person decrease in the number of chronically
homeless per 100,000 population” (Moulton, 2013, p. 602).

Though his analysis did not specify different uses for this funding or attempt to
differentiate the cost-effectiveness of different types of programs, he did suggest that “programs
that provide long-term housing and services to homeless people with disabilities drives [sic] this
relationship [between increased funding and reduced chronic homelessness rates]” (Moulton,
2013, p. 602). My analysis expands beyond Moulton’s because it includes the years 2007 to
2016, whereas Moulton’s includes only 2005 to 2007. Furthermore, while Moulton focuses on
cost-effectiveness, dollars to outcomes, my study seeks to measure specific program effectiveness while controlling for funding.

Housing First

A majority of programs historically used to serve the homeless utilize delivery models that require “housing readiness,” a concept that combines sobriety, medication and health treatment compliance, income source, and other similar baseline requirements to ensure successful transition out of homelessness (Tsembris, Gulcur, & Nakae, 2004). This model assumes that individuals with chronic illness, mental illness, or substance abuse disorders cannot live independently without first managing these conditions, and places those individuals at risk of being dropped from services if any of the conditions resurface.

The Housing First model emerged as a response to these limitations. Developed by Dr. Sam Tsembris, Housing First is “based on the belief that housing is a basic right and on a theoretic foundation that includes psychiatric rehabilitation and values consumer choice” (Tsembris, Gulcur, & Nakae, 2004, p. 651). Since its initial implementation in 1999, Housing First has been widely used as a method to address homelessness among the population with mental illness and/or substance abuse diagnoses (Stefanic & Tsembris, 2007).

Since the advent of the Housing First model, there has been plentiful anecdotal and experiential evidence of both quality of life improvements and cost-effectiveness, but few quantitative analyses. Because the model aligns with the long-term intervention model included this paper, understanding the effectiveness of Housing First programs is useful background.

In 2010, Jack Tsai, Alvin S. Mares, and Robert A. Rosenheck surveyed both patients of
residential treatment (“Residential Treatment First”) and recipients of Housing First services to compare the two populations on housing stability post-intervention (Tsai et al., 2010). The researchers studied 709 clients of organizations that received grant funding from the U.S. Interagency Council on Homelessness (USICH), an inter-agency body of the Executive Branch authorized by the McKinney-Vento Act of 1987 to coordinate the federal response to homelessness. The USICH grants were designed to establish collaborative partnerships to reduce the prevalence of chronic homelessness in each geographic jurisdiction. Success was measured by number of days within the past three months in which subjects were housed in different places: own home, hotel, transitional house, residential program, outdoors, jail, and so forth. There were also metrics for community adjustment, measured primarily by participation in community activities ranging from visiting a grocery store to attending a local event or visiting a neighbor’s house.

Tsai, Mares, and Rosenheck found that Housing First clients spent more days at home and fewer days incarcerated than Residential Treatment First clients, and reported higher self-assessed satisfaction. There was no significant difference between the two groups in number of days homeless in the past three months, but the mean was less than five for all groups (Tsai et al., 2010).

Though this study suggests that Housing First produces more stable housing for the populations studied, there were substantial characteristic differences between the two groups, particularly in the metric of dual diagnoses, so randomized control studies with more consideration of group characteristics are needed to better understand the true effectiveness of

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1 About USICH. (n.d.)
Housing First, compared to Residential Treatment First.

Other analyses have focused on success of Housing First with veterans. One such study, conducted by Ann Elizabeth Montgomery, Lindsay L. Hill, Vincent Kane, and Dennis P. Culhane compared Housing First to “Treatment As Usual” (TAU) for veterans experiencing homelessness (2010). This study compared “low demand” and “high demand” services. Low demand refers to programs like Housing First, which involve no requirements of sobriety or service compliance, and are dedicated to the principles of consumer choice. High demand services require housing readiness, as described above (Montgomery et al., 2013).

Through observation and survey of 107 Housing First recipients, 74 percent of whom were chronically homeless, and 70 TAU participants, 63 percent of whom were chronically homeless, Montgomery et al. found that Housing First clients moved into permanent housing significantly faster than TAU clients (167.9 days faster). Housing First had a 98 percent retention rate one year into the program while TAU had a retention rate of 86 percent, and Housing First clients were eight times more likely to be housed stably after twelve months than TAU clients. Both groups also had large decreases in urgent care visits, although there was no statistically significant difference between the two programs for this metric (Montgomery et al., 2013).

Similar to Tsai et al.’s study, this approach provides further evidence for the effectiveness of Housing First in moving people experiencing homelessness toward stable, permanent housing, within this particular population.

*Permanent Supportive Housing*

Housing First, as a model, is most often used alongside Permanent Supportive Housing
programs. According to the USICH, Permanent Supportive Housing (PSH) “combines non-time-limited affordable housing assistance with wrap-around supportive services for people experiencing homelessness, as well as other people with disabilities.” PSH is a holistic approach to combating homelessness, in which people receive housing assistance in addition to case management services as further support to ensure they are successful in their transition out of homelessness. Sometimes this support is offered in a single building, where residents live and receive services on site, and other times residents rent apartments on the private market using subsidies, and receive services at a separate site. The key parts of PSH are its duration—there are no time limits on service provision—and its supportive nature—the services focus on housing in addition to other health, wellness, financial security, and job readiness goals. Figure 4 shows the increase in availability of PSH services in the past decade, demonstrating the nationwide trend of increased popularity for this style of intervention.

Figure 4: Trend in National Availability of PSH Beds. (Source: HIC 2007-2016)

Supportive Housing (2016).
Because of its intensive wrap-around services, PSH is most often utilized as an intervention for particularly vulnerable populations, such as those with severe mental illness, as the assertive nature of the program provides added support to individuals who face higher obstacles to success in independent housing (Leff et al., 2009). A meta-analysis of studies evaluating the impacts of housing-plus-service models for clients with mental illness, conducted by H. Stephen Leff, Clifton M. Chow, Renee Pepin, Jeremy Conley, I. Elaine Allen, and Christopher A. Seaman, found that these intensive services such as PSH, residential care housing, and treatment housing, all had significant positive impacts on housing stability (2009). Each of these interventions, which would be classified as “long-term interventions” in my analysis, led to significant decreases in client hospitalization. PSH was found to have the strongest effects in both stability and decreased hospitalization, in addition to significant improvement in self-reported client satisfaction (Leff et al., 2009).

Certain cities have been especially successful in implementing PSH effectively. In a comprehensive, multi-part evaluation of a specific campaign in Los Angeles to reduce chronic homelessness using PSH, the Urban Institute’s Martha Burt drew positive conclusions about the effectiveness of this model (Burt, 2009). Burt found that the Corporation for Supportive Housing (CSH) was able to effectively reduce long-term homelessness in LA County, particularly among individuals with mental illness, using a combination of development projects for PSH and collaboration between public officials and community organizations to build a coalition of support for PSH interventions (Burt, 2008). Burt utilized a combination of government data, data from CSH, and surveys to evaluate the success of this campaign. Final analysis revealed that the program achieved significant reductions in numbers of chronically homeless individuals, wider
sources of funding for PSH, and a broader coalition of support for supportive housing interventions. However, the scope of the problem in Los Angeles County remains large, and the report called for increased investment of public dollars in the project (Burt, 2009).

Similarly, in a review of community investment in PSH and its impact on chronic homelessness, Thomas Byrne, Jamison D. Fargo, Anne Elizabeth Montgomery, Ellen Munley, and Dennis P. Culhane found a statistically significant, yet modest, relationship between investment in PSH and rates of chronic homelessness (2014). Their Poisson regression revealed “that an increase of one PSH unit per every 10,000 adults in a community is associated with a 1 percent decrease in its total rate of chronic homelessness per 10,000 adults” (Bryne et al., 2014, p. 249). These results are closely related to the hypothesized results of my analysis, although Bryne et al. used data from 2007 to 2012 and measured rates of chronic homelessness against number of PSH units, rather than numbers of chronic homeless against a grouped proportion of multiple permanent interventions.

**Rapid Re-Housing**

The most recent addition to the effort to combat homelessness is Rapid Re-Housing (RRH), a program designed to immediately stabilize homeless families by re-housing them and using financial support to keep them housed until they are able to pay rent independently (Fisher, Mayberry, Shinn, & Khadduri, 2014). RRH was initiated nationwide in 2009 as part of the American Reinvestment and Recovery Act, and officially concluded in 2012, although some communities used the model before 2009 and continue to after 2012.

Similar to Housing First and PSH, little data exist on the effectiveness of the Rapid Re-
Housing program (RRH). One analysis, conducted by Thomas Byrne, Dan Treglia, Dennis P. Culhane, John Kuhn & Vincent Kane, sought to evaluate the RRH program within a population of veterans (Byrne et al., 2015). Byrne et. al utilized data from the Supportive Services for Veteran Families program (SSVF), which serves both independent veterans and veterans in families with temporary financial assistance to help prevent homelessness and quickly stabilize those experiencing homelessness. SSVF prioritizes RRH over prevention, as 60 percent of funds must be spent on RRH, according to the financial structure of the program (Bryne et al., 2015).

Byrne et al. found that both the prevention and RRH services effectively reduced rates of homelessness at both the one- and two-year post-service mark. However, veterans in families had lower homelessness rates than independent veterans, and those with prevention services had lower rates than those with RRH services (2015). This study is limited in its external validity, however, because it is specific to veterans leaving this program, and limited in its internal validity because there was no counterfactual. The rates of returning to homelessness upon exiting SSVF in this study compare favorably with rates of return to homelessness among individuals exiting emergency shelter (Byrne et al., 2015); however, this study does not specify these statistics for veterans themselves, just for the general population.

One piece of relevant analysis from Byrne et al.’s study was the risk analysis. A timeline map measuring the risk of returning to homelessness among the veterans in the study suggested that the associated risk of returning was highest in the first ninety days after exit from the program. If veterans were able to move through that period, their risk of returning to homelessness decreased (Byrne et al., 2015). This suggests that extending services longer or developing a slower weaning period might be beneficial for increasing retention in housing.
A final study of note relating to the topics covered in my analysis concerns an effort to understand human behavior involved in homelessness interventions. In an analysis conducted by Benjamin W. Fisher, Lindsay S. Mayberry, Marybeth Shinn, and Jill Khadduri, 2,037 families in time-limited homeless shelters in twelve different geographic regions were recruited and divided randomly into four groups: usual care (control group), project-based transitional housing, permanent subsidy (Housing Choice Voucher), and temporary subsidy (RRH) (Fisher et al., 2014). Families were offered the randomly selected service and the opportunity to either accept or decline that service. The researchers then interviewed the families to determine why they made the choices they did.

Fisher, Mayberry, Shinn, and Khadduri determined that location was an important factor in determining whether people chose to accept or reject the offer (2014). Stability was also critical, as many families chose to forgo transitional shelter in favor of emergency shelter because of the relative permanency of the emergency beds: they knew they were able to remain in place in the emergency shelter, despite poor conditions, whereas transitional housing had a strict end date. Similar feelings of anxiety were reported with RRH because of inherent recertification requirements. The most frequently accepted option, and the option with highest reported satisfaction rate, was the permanent subsidies (Fisher, et al., 2014).

Though this study cannot be considered a true randomized control trial, as the sample consists of only sheltered homeless families, as opposed to the entire sheltered and unsheltered homeless population, the results support the hypothesis of my analysis: that long-term interventions (not emergency or transitional, in particular) will be more successful in reducing chronic homelessness because high client satisfaction will cause regular service utilization,
yielding lasting outcomes.

My analysis contributes to the existing literature in two key ways: substance and scope. My study is unique in that it assesses all anti-homelessness interventions in two broad categories, rather than the more common approach of evaluating one specific program at a time. I evaluate all services designed to address homelessness by creating two categories: short- and long-term, or services that are time-limited and those that are not. Rather than focusing specifically on RRH or PSH, as other studies do, my research groups these together, along with other permanent housing programs, into a category I call “long-term interventions.” By grouping all long-term services together, I seek to understand whether, methodologically, non-time-limited interventions are a more effective means by which to combat chronic homelessness than emergency and transitional services.

Furthermore, no existing study utilizes all ten years of available HIC and PIT data on a national level. Any evidence that currently exists supporting the effectiveness of long-term programs limits the geography, the time range, or the type of program. My analysis spans ten years, over 390 Continuums of Care, and explores more programs than any existing paper. With this research, I hope to lend quantitative evidence to the currently anecdotal and theoretical understanding that non-time-limited services more successfully battle chronic homelessness than emergency relief.

I turn next to the theoretical framework that guides my analysis.
THEORETICAL MODEL

The existing studies on interventions to combat homelessness, discussed above, all include similar factors as inputs. I drew on this research in creating my own model for this study of the effectiveness of long-term interventions in reducing counts of the chronically homeless population. I developed a theoretical model that takes into account a variety of categories of factors that should impact rates of chronic homelessness. The model is as follows:

\[
\text{Count of Chronically Homeless} = f (\text{Services, Funding, Demographics})
\] (1)

The dependent variable, number of chronically homeless individuals in the population, will first be a function of the types of services offered that seek to combat chronic homelessness in that CoC. In this model, that variable takes the form of a proportion: the number of beds available for long-term services as a fraction of the total beds offered, as reported in the Housing Inventory Count. This variable is labeled sharelong in the Empirical Model below. For example, if a given CoC offers 10 PSH beds, 2 RRH beds, 15 emergency shelter beds, and 7 transitional housing beds, the long-term proportion would be 12/34, or 0.3529. In 2016, Washington DC (CoC #DC-500) offered a total of 8,314 short-term beds and 12,687 long-term beds, so the sharelong measure for this CoC in this year was 0.6041.

I chose to use proportions, rather than discreet numbers, in order to measure the degree of emphasis on long-term services versus short-term services in that CoC. If this study were measuring the availability of services generally, rather than emphasis on one type over the other, the discreet bed-count could be used for this measure. Furthermore, using a proportional measure allows for differentiation between CoCs that provide a lot of beds generally and those that
provide fewer overall but heavily emphasize long-term beds. Whereas CoC DC-500’s 12,287 long-term beds is a far smaller number than New York City’s (CoC NY-600) 29,650 long-term beds, NY-600 provides such a high total number (102,695) that this high long-term number only accounts for a 0.2887 portion of the total beds. Therefore, DC-500’s emphasis on long-term services and NY-600’s emphasis on short-term is represented here.

Total count of chronically homeless individuals will also be a function of the funding allocated to combating homelessness in that CoC. In this model, grant funding allocated from HUD to the given CoC, as part of the annual funding availability competition, is used as a control variable. Previous studies have assessed the correlation between funding availability and reductions in counts of the homeless population (Moulton, 2013), so controlling for grant allocation in this model is critical for reducing the impact of potential omitted variable bias. Further discussion of the methodology behind this variable is provided in the next section.

Finally, community characteristics are also expected to play a role in determining total numbers of chronically homeless individuals in a CoC. Demographic and economic indicators taken from ACS are used as controls in this model. These demographics include factors that may influence homeless numbers such as area median income, poverty rate, unemployment rate, median rent, homeownership rate, veteran population, racial composition, and CoC population. These economic indicators specifically will also help account for effects of financial crisis, housing crisis, and other such time-related events that could skew the results.

With these theoretical concepts in mind, I turn now to a description of the empirical model I use to implement my analysis.
EMPIRICAL MODEL

To test my hypothesis that a higher share of long-term services offered leads to lower counts of chronically homeless individuals, I pulled the concepts from the theoretical model into four empirical models, including two pooled OLS and two Fixed Effects models.

\[
\text{totalchronic} = B_0 + B_1 \times \text{sharelong} + B_2 \times \text{grant} + B_3 \times \text{income} + B_4 \times \text{rent1bdrm} + \\
B_5 \times \text{ownshare} + B_6 \times \text{poverty} + B_7 \times \text{uerate} + B_8 \times \text{veteran} + B_9 \times \text{nonwhite} + \\
B_{10} \times \text{population} + E
\]  

I test the above model using both pooled OLS and Fixed Effects techniques. There could be unobserved time invariant characteristics specific to each CoC that introduce bias into the pooled OLS model, suggesting a potential need for Fixed Effects. The variables remain the same in both models, and both models span the years 2007 to 2016.

The key dependent variable, \textit{sharelong}, is a continuous variable measuring the availability of long-term beds as a share of total beds available in the CoC. Methodology for creating this variable is further explained in the Theoretical Model section above, as well as in the Data section below. I expect to see a negative coefficient, indicating that as share of total beds allocated to long-term interventions increases, total number of chronically homeless individuals will decrease.

The first control variable, \textit{grant}, is a continuous variable indicating the total amount of grant funding that CoC received from HUD in the previous year. This variable is lagged, so the grant allocation from 2006 is matched with the observations from 2007 for all other variables for each CoC. I created this lagged measure because funding allocated in FY06 should not see return until at least the 2007 PIT count. I also expect a negative coefficient estimate for \textit{grant}, suggesting that higher grant allocation corresponds to a decrease in total numbers of chronically
homeless individuals. Existing research supports the idea that increased funding for homeless services decreases homelessness generally.

The next set of variables measure economic characteristics in the community. There could be a correlation between economic indicators in the community and the number of chronically homeless individuals in the CoC, so it is necessary to pull them out of the error term as their own variables to control for potential endogeneity. I expect income to have a negative coefficient, as areas with higher median incomes should see lower levels of chronic homelessness. The coefficient on rent1bdrm, the measure of median rent for a one-bedroom unit in the area, will likely have a positive coefficient, as the higher local rents are, the harder it is for a homeless individual to transition out of homelessness without assistance, and therefore the higher I expect the count of people experiencing chronic homelessness to be. I also expect the share of homeowners in the population, ownshare, to have a negative coefficient, as a healthy housing market, with high homeownership rate should correlate with fewer long-term homeless people. The portion of the population below the poverty line, poverty, is expected to have a positive coefficient, as areas with a higher poverty rate will have higher homelessness counts, and a higher unemployment rate, uerate, should also correspond with higher counts of homeless individuals, as fewer jobs in the area will likely lead to more people in a situation of homelessness.

The final set of variables includes demographic characteristics of the CoC as added controls to lessen the chance of omitted variable bias. The portion of veterans who are homeless tends to be higher than the portion of the general population who are homeless, so I estimate the coefficient on veteran, the portion of the adult population who are veterans, to be positive. There
is little existing research or theory behind how population size or race affect rate of chronic homelessness, so it is uncertain whether the variables *nonwhite* (a measure of the portion of the CoC population that is a race other than white, as reported in ACS) and *population* (total population of the CoC) will be have positive or negative coefficients.

\[
totalchronic = B_0 + B_1*lsharelong + B_2*grant + B_3*income + B_4*rent1bdrm + \\
B_5*ownshare + B_6*poverty + B_7*u rate + B_8*veteran + B_9*nonwhite + \\
B_{10}*population + E
\]  

This second model is identical to the first, except for the key independent variable, *lsharelong*. This is a lagged measure of the same key variable above, measuring the share of beds in the CoC devoted to long-term services in the year before. I also consider this model using both pooled OLS and Fixed Effects, but because of the lag, only the years 2008 to 2016 are included. I expect the lagged *lsharelong* variable to have a negative coefficient for similar reasons as discussed above. I anticipate the magnitude of the coefficient to be lower than in the same-year measure, because looking at the manifestation of a program a year later will allow for other factors to influence the results. The count of chronic homelessness in one year will be affected by more unobserved factors when measured against share of beds devoted to long term services the year before versus the current year. For example, there could be a crisis contributing to an increase in people experiencing homelessness or there could be a lag in utilization of services provided in a given year.\(^k\) Thus, I expect the coefficient on the lagged variable to indicate a more

\(k\) This lagged measure also helps account for people who may drop out of a housing program within the first year. Anyone who is placed into housing via short- or long-term service would be counted as chronically homeless in the following year’s PIT Census, so this lag helps ensure
modest relationship to account for these unobserved and unexpected factors.

I do not anticipate any of the other coefficients to change between the two models, non-lagged and lagged, so predictions for all of the other variables described above hold. The final analysis contains four models: pooled OLS and FE estimates of equation (2) and pooled OLS and FE estimates of equation (3).

In the following section I discuss the data used to measure each of the variables in the above models.
DESCRIPTION OF DATA

Data for this study come from two sources: the U.S. Department of Housing and Urban Development (HUD) and the U.S. Census Bureau. I compiled data from four different public use data sets to create a master panel data set spanning the years 2007 to 2016 with a total of 4,423 observations. A table of descriptive statistics is included at the end of this section (Table 2).

The HUD data come in two parts: PIT Census and HIC. The Point-in-Time Census (PIT) is the yearly count of all persons experiencing homelessness within each Continuum of Care. Every year, each CoC coordinates volunteers to canvas their communities on one night in the last ten days of January, to count all unsheltered homeless individuals within their jurisdictions. Volunteers engage with people experiencing homelessness to record demographic characteristics and experienced CoC staff review surveys to ensure no people are double-counted. Simultaneously, on the same night, all shelters in the CoC report numbers of current shelter residents fitting into each category. These data are reported to HUD and centralized into one large data set, which includes counts for total sheltered and unsheltered homeless individuals, broken down into distinct categories. Though the exact categories vary yearly, they include families, individuals, number of people in families, chronically homeless, and in later years, veterans and unaccompanied youth. The dependent variable in this study, Total Chronically

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m On January 11th, 2017, I attended the official volunteer training for the 2017 PIT Census in Washington, D.C. where representatives from The Community Partnership, the DC-500 CoC organizing body, reviewed the methodology of the PIT Census in detail. This training and instruction are standardized across the country and across years, and the importance of accuracy in methodology was strongly emphasized. This experience, in addition to detailed reading of methodology guides, provides reassurance regarding the reliability of these data.
Homeless (totalchronic) comes from this PIT data set.\(^n\)

The Housing Inventory Count (HIC) is a comprehensive list of all homeless services available within a CoC. Each CoC conducts this inventory independently, within one week of the PIT count, to ensure the two counts match as closely as possible.\(^o\) Though categories vary by year, they include emergency shelter, transitional shelter, Safe Haven housing, Permanent Supportive Housing, and Rapid Re-housing. Figure 5, below, shows national trends in allocation of each of these types of beds. Each category is further divided into seasonal, year-round, those specified for domestic violence victims, and others. I focused on the “total beds” in each

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\(^n\) Though the PIT Methodology Guide specifies that the unsheltered PIT count must occur only biennially, in “odd-numbered” years, the data indicate only 4, 5, 7, 3, and 8 CoCs did not report unsheltered counts in 2008, 2010, 2012, 2014, and 2016 respectively, so lack of reporting is not a concern for validity in these data.

\(^o\) 2016 Housing Inventory Count and Point-in-Time Count of Homeless Persons: Data Submission Guidance (2016).
category, because specifying beds for other purposes was outside the scope of my analysis.

Using these “totals” categories, I created new variables to serve as key independent variables in the study: Total Beds ($\text{totalbeds}$), Total Long-Term Beds ($\text{totallong}$), Total Short-Term Beds ($\text{totalshort}$), share of Total Beds that are “short-term” ($\text{shareshort}$), and share of Total Beds that are “long-term” ($\text{sharelong}$). The $\text{totalbeds}$ variable was created by adding together all the “total” counts for each category in each year. Similarly, I created the $\text{totallong}$ variable by adding all beds available for the permanent interventions—those designed to be non-time-limited rather than temporary, emergency relief—and the $\text{totalshort}$ variable by adding all beds available for temporary purposes. In 2007 to 2012, $\text{totallong}$ included only Permanent Supportive Housing beds, while the $\text{totalshort}$ included emergency shelter, transitional housing, and Safe Haven. In 2013 the long-term category included Rapid Re-Housing as well. And in 2014 to 2016, a new category of “Other Permanent Housing” was added. Finally, I created the $\text{sharelong}$ variable to

Figure 6: National Trend in Availability of Short- vs. Long-Term Beds.  
(Source: HIC 2007-2016)
measure number of long-term beds as a percent of total beds available, and the \textit{Isharelong} variable as a one-year lagged measure of the share of beds that are long-term in the previous year. Figure 6 shows how the share of short-term beds and share of long-term beds changed over the ten years in this analysis. Since 2007, the share of long-term beds nationwide has steadily increased to just over half in 2016.

The changes in categories within both PIT and HIC data over time, as well as the changes in PIT counting methodology, could act as a potential limitation in these data. Similarly, because the PIT count is conducted by volunteers, who may become more accurate across time as techniques of counting unsheltered individuals become more advanced, there could be an additional concern about bias resulting from measurement error in the study. However, according to the official methodology guides distributed by HUD to each CoC, volunteers must go through a rigorous training process where they learn stringent methodology guidelines for the census. These guidelines are standardized across the country, so any error that exists in one CoC will be consistent across all CoCs. Furthermore, volunteers for the PIT count are accompanied by professional outreach staff to ensure the volunteers are able to locate all potential sites of unsheltered homeless people and engage with them in a meaningful way, to record the appropriate demographic information.

Additionally, there are multiple layers of HUD review both prior to the count and after data submission to mitigate potential discrepancies. When reviewing data submission, HUD checks whether the subtotal of persons reported in emergency shelter, Safe Haven, and transitional housing match the total of sheltered persons reported in the PIT count for each CoC. If there are discrepancies, the CoC is contacted for changes. This process serves as an internal
source of data validation, helping to eliminate some of the concern for human error in this data collection. Similarly, the uniform methodology guide serves to maximize the uniformity of the data collection system across time and place, to again correct for any human error present.\(^p\) Because of these internal controls in place, I believe the HIC and PIT data to be reliable for the purposes of this analysis.

The third data set retrieved from HUD is the CoC Grant Allocation. Every year, agencies within each CoC apply for grant funding to provide and coordinate their services, and HUD publishes a comprehensive list of these grant awards each year. These awards are broken down to the level of which specific agency received each grant, so I created subtotals for each CoC and used those subtotals as a control variable in the model. For example, each agency receiving grant funding within the AK-500 jurisdiction was added together to form one subtotal for the AK-500 grant observation for each year. Because grant money awarded in 2006 would manifest itself in 2007, I matched the grant amounts from the year prior into the model, including grants from 2006 to 2015, and then recoded each observation so that those grants from 2006 would align with observations from 2007, those from 2007 would align with observations from 2008, and so forth.

Finally, I collected data from the American Community Survey (ACS) to add demographic information as further controls for each CoC. Through collaboration with researchers at HUD, each of 11,078,297 census blocks from the 2014 ACS were assigned to corresponding CoCs using GIS overlay. Once these census blocks were matched with the appropriate CoC, ACS micro-data were used to extract demographic information for each CoC.

\(^p\) “HDX FAQs” (n.d.).
The variables include median household income, median gross rent, share of owner vs. renter households, share of population with different education levels, share of veterans, share of households below the poverty line, unemployment rate, and race and sex breakdowns. Data from the 2016 ACS were not available at the time of this analysis, so one year of data are missing demographic characteristics. Leaving 2016 PIT, HIC, and grant data out of the analysis would cause the data set to lose over 400 observations, so I estimated the 2016 ACS data by duplicating the 2015 data for each CoC. I discuss the tests I ran to determine the validity of this estimation in the Sensitivity Analysis section at the end of this paper.

Before going into detailed discussion of the key dependent and independent variables in this model, it is important to note one limitation of these data. I have already discussed missing demographic data 2016, and in the process of merging data sets I discovered missing grant data as well. This missing data can be explained by recognizing that not all CoCs received grant funding each year. The missing data in HIC and PIT data sets is a larger concern. Both HIC and PIT rely upon submission from CoCs for complete datasets, and for each year there are certain CoCs who fail to report either PIT or HIC data. Table 1, below, shows how many CoCs did not report either PIT or HIC each year, as well as the total number of CoCs in that year.

<table>
<thead>
<tr>
<th>Year</th>
<th># w/out HIC</th>
<th># w/out PIT</th>
<th>Total CoCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>17</td>
<td>77</td>
<td>479</td>
</tr>
<tr>
<td>2008</td>
<td>15</td>
<td>66</td>
<td>464</td>
</tr>
<tr>
<td>2009</td>
<td>11</td>
<td>60</td>
<td>459</td>
</tr>
<tr>
<td>2010</td>
<td>12</td>
<td>53</td>
<td>459</td>
</tr>
<tr>
<td>2011</td>
<td>17</td>
<td>50</td>
<td>450</td>
</tr>
<tr>
<td>2012</td>
<td>9</td>
<td>34</td>
<td>437</td>
</tr>
</tbody>
</table>

Table 1: Missing HIC and PIT Data.
The numbers above show that in comparison to the total number of CoCs, the rate of non-reporting is minimal, so the lack of data submission should not bias results. I dropped the CoCs with missing data from my regression, which is a practice consistent with other analyses using these data (Moulton, 2013). To add another level of sensitivity to this decision, I ran tests to determine whether these CoCs missing data had shared characteristics. To assess potential problems with missing HIC data, I used graphical analysis to compare all CoCs with more than one year of missing HIC data in order to identify whether there are shared characteristics that could lead to suspicion of selection bias if these data are left out of the final regressions. Comparison of income, population, unemployment rate, population of color, poverty rate, and share of homeowners revealed no concern for selection bias. There were no trends to indicate these CoCs share characteristics in common, and comparison of these CoCs with the CoCs with one missing year or less also lacked evidence to suggest that removing these CoCs with missing observations from the final data set would cause a concern for selection bias.

To assess CoCs with missing PIT data, I observed no pattern for which CoCs submitted data in given years and which did not. There are four CoCs without any PIT data for all ten years: CT-502, KS-501, MO-604, and NY-502. A query of data officials at HUD produced no

---

Table 1: Missing HIC and PIT Data. (cont.)

<table>
<thead>
<tr>
<th>Year</th>
<th># w/out HIC</th>
<th># w/out PIT</th>
<th>Total CoCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>8</td>
<td>30</td>
<td>429</td>
</tr>
<tr>
<td>2014</td>
<td>3</td>
<td>22</td>
<td>418</td>
</tr>
<tr>
<td>2015</td>
<td>14</td>
<td>17</td>
<td>421</td>
</tr>
<tr>
<td>2016</td>
<td>4</td>
<td>4</td>
<td>407</td>
</tr>
</tbody>
</table>

---

q CoC with missing HIC data are as follows: AR-503 (missing 2007 to 2009), GA-502 (missing 2007 to 2012), GA-508 (missing 2007 to 2012), LA-509 (missing 2007 to 2014), and PA-512 (missing 2007-2010).
insight into why these CoCs did not submit any PIT data for these years,⁷ and analysis of the demographic characteristics of these four CoCs revealed no clear patterns or distinctions. As a result, I also dropped these four CoCs from my analysis.

Finally, though CoCs are reallocated each year, according to changing partnerships and populations, fewer than fifteen new CoCs are created or collapsed each year, causing little disruption in the analysis.

Table 2: Descriptive Statistics for All Variables⁸

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>totalhomeless</td>
<td>Total homeless (families and individuals)</td>
<td>3,997</td>
<td>1,521.43</td>
<td>3,880.43</td>
<td>4</td>
<td>75,323</td>
</tr>
<tr>
<td>sheltered</td>
<td>Total sheltered homeless</td>
<td>3,997</td>
<td>982.70</td>
<td>3,045.34</td>
<td>0</td>
<td>72,140</td>
</tr>
<tr>
<td>unsheltered</td>
<td>Total unsheltered homeless</td>
<td>3,997</td>
<td>538.73</td>
<td>1,645.73</td>
<td>0</td>
<td>36,420</td>
</tr>
<tr>
<td>individ</td>
<td>Total homeless individuals</td>
<td>3,997</td>
<td>954.78</td>
<td>2,301.70</td>
<td>0</td>
<td>44,185</td>
</tr>
<tr>
<td>totalplinfam</td>
<td>Total homeless people in families</td>
<td>3,997</td>
<td>566.64</td>
<td>1,939.48</td>
<td>0</td>
<td>45,711</td>
</tr>
<tr>
<td>totalchronic</td>
<td>Total chronically homeless individuals</td>
<td>3,997</td>
<td>267.36</td>
<td>748.65</td>
<td>0</td>
<td>19,031</td>
</tr>
<tr>
<td>shelteredchronic</td>
<td>Total sheltered chronically homeless individuals</td>
<td>3,997</td>
<td>101.79</td>
<td>207.93</td>
<td>0</td>
<td>3,794</td>
</tr>
<tr>
<td>unshelteredchronic</td>
<td>Total unsheltered chronically homeless individuals</td>
<td>3,997</td>
<td>165.57</td>
<td>625.74</td>
<td>0</td>
<td>17,427</td>
</tr>
<tr>
<td>vets</td>
<td>Total homeless veterans</td>
<td>2,403</td>
<td>132.56</td>
<td>312.67</td>
<td>0</td>
<td>6281</td>
</tr>
<tr>
<td>totalbeds</td>
<td>Total beds available</td>
<td>4,303</td>
<td>1,657.00</td>
<td>4,596.30</td>
<td>6</td>
<td>104,296</td>
</tr>
<tr>
<td>sharelong</td>
<td>Total long term beds divided by total beds</td>
<td>4,303</td>
<td>0.3550</td>
<td>0.1885</td>
<td>0</td>
<td>0.9035</td>
</tr>
<tr>
<td>issharelong</td>
<td>Sharelong variable lagged 1 year</td>
<td>3,882</td>
<td>0.3413</td>
<td>0.1826</td>
<td>0</td>
<td>0.8818</td>
</tr>
</tbody>
</table>

⁷ Email query sent to HUD Exchange Data Program Support on November 2nd, 2016 with response on December 14th, 2016.
⁸ Variables used in final analysis are highlighted.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>shareshort</td>
<td>Total short term beds divided by total beds</td>
<td>4,303</td>
<td>0.6450</td>
<td>0.1885</td>
<td>0.0965</td>
<td>1</td>
</tr>
<tr>
<td>totallong</td>
<td>Total PSH, OPH, RRH beds</td>
<td>4,303</td>
<td>672.46</td>
<td>1,708.49</td>
<td>0</td>
<td>29650</td>
</tr>
<tr>
<td>totalshort</td>
<td>Total ES, TH, SH</td>
<td>4,303</td>
<td>984.54</td>
<td>3070.73</td>
<td>5</td>
<td>75,068</td>
</tr>
<tr>
<td>totalyearroundshort</td>
<td>Total Short-term beds minus seasonal beds</td>
<td>4,303</td>
<td>989.15</td>
<td>3073.61</td>
<td>5</td>
<td>75,068</td>
</tr>
<tr>
<td>emergencytotal</td>
<td>Total emergency shelter beds</td>
<td>4,303</td>
<td>541.72</td>
<td>2590.344</td>
<td>0</td>
<td>69,927</td>
</tr>
<tr>
<td>transitionaltotal</td>
<td>Total Transitional Housing beds</td>
<td>4,303</td>
<td>438.45</td>
<td>760.09</td>
<td>0</td>
<td>10,094</td>
</tr>
<tr>
<td>pshtotal</td>
<td>Total Permanent Supportive Housing beds</td>
<td>4,303</td>
<td>610.41</td>
<td>1599.41</td>
<td>0</td>
<td>28,640</td>
</tr>
<tr>
<td>safehaven</td>
<td>Total Safe Haven beds</td>
<td>3,842</td>
<td>4.89</td>
<td>13.20</td>
<td>0</td>
<td>165</td>
</tr>
<tr>
<td>rrhtotal</td>
<td>Total Rapid Re-Housing beds</td>
<td>1,642</td>
<td>118.81</td>
<td>309.49</td>
<td>0</td>
<td>3,824</td>
</tr>
<tr>
<td>ophtotal</td>
<td>Total Other Permanent Housing beds</td>
<td>1,222</td>
<td>58.87</td>
<td>240.65</td>
<td>0</td>
<td>2806</td>
</tr>
<tr>
<td>grant</td>
<td>Grant allocation</td>
<td>4,257</td>
<td>$3,758,172</td>
<td>$8,109,473</td>
<td>$1,998</td>
<td>$122,000,000</td>
</tr>
<tr>
<td>income</td>
<td>Median Household Income (for occupied units where household income &gt;0)</td>
<td>3,125</td>
<td>$53,129.92</td>
<td>$14,015.64</td>
<td>$25,000</td>
<td>$122,000</td>
</tr>
<tr>
<td>rent1bdrm</td>
<td>Median gross rent for 0 to 1 bedroom units</td>
<td>3,125</td>
<td>$672.67</td>
<td>$205.42</td>
<td>$298</td>
<td>$1,702</td>
</tr>
<tr>
<td>rent2bdrm</td>
<td>Median gross rent for 2 bedroom units</td>
<td>3,125</td>
<td>$869.99</td>
<td>$251.17</td>
<td>$474</td>
<td>$2,103</td>
</tr>
<tr>
<td>rent3bdrm</td>
<td>Median gross rent for 3 or more bedroom units</td>
<td>3,125</td>
<td>$1,119.46</td>
<td>$339.16</td>
<td>$537</td>
<td>$2,543</td>
</tr>
<tr>
<td>ownshare</td>
<td>Share of owner households</td>
<td>3,125</td>
<td>0.6570</td>
<td>0.0949</td>
<td>0.2218</td>
<td>0.8638</td>
</tr>
<tr>
<td>rentshare</td>
<td>Share of renter households</td>
<td>3,125</td>
<td>0.3429</td>
<td>0.0949</td>
<td>0.1362</td>
<td>0.7782</td>
</tr>
<tr>
<td>edu_hs</td>
<td>Share of people 18 and older with high school diploma or GED</td>
<td>3,125</td>
<td>0.1330</td>
<td>0.0489</td>
<td>0.0410</td>
<td>0.3749</td>
</tr>
<tr>
<td>edu_isHS</td>
<td>Share of people 18 and older without high school diploma or GED</td>
<td>3,125</td>
<td>0.2897</td>
<td>0.0620</td>
<td>0.0926</td>
<td>0.4454</td>
</tr>
</tbody>
</table>
The key dependent variable in this model, highlighted in the table above, is totalchronic, a count of all chronically homeless individuals and individuals in families, taken from the PIT data set.\(^ {1}\) The focus of long-term interventions is ending homelessness for the chronically homeless specifically, so count of chronically homeless will be the dependent variable of interest. Similarly, the goal of the U.S. Interagency Council on Homelessness is to end chronic homelessness by 2017, so the total number of chronically homeless individuals within a CoC is an appropriate dependent variable for this study.\(^ {u}\)

The key independent variables of interest in the model, also highlighted in the table

\(^ {1}\) As noted above, chronically homelessness is defined as having experienced homelessness for more than a year or more than four times in the past three years.

\(^ {u}\) Opening Doors: Federal Strategic Plan to Fight and End Homelessness, as Amended in 2015 (2015), page 6.
above, are the created variable \textit{sharelong} and the lagged \textit{lsharelong}, from the HIC data set. The analysis is designed to investigate whether those jurisdictions that focus on long-term interventions over emergency and transitional services are more successful in combating chronic homelessness, so I focus predominantly on the relationship between these variables and \textit{totalchronic} when interpreting the results. The grant funding information from HUD and the demographic information from the ACS data set are included as controls in the model, as described in the Empirical and Theoretical Model sections above.

I now turn to my results.
RESULTS

Each of the four models considered in the final analysis is statistically significant, with an F-statistic significant at the 99 percent level, and key variables of interest significant at the 99 percent or 95 percent level. These results indicate there is a statistically significant, negative relationship between \( \text{sharelong} \) and the dependent variable \( \text{totalchronic} \), and between the lagged \( l\text{sharelong} \) and \( \text{totalchronic} \). This relationship suggests that higher use of long-term interventions to combat homelessness correlates with lower counts of chronically homeless individuals. Results for the two key independent variables, \( \text{sharelong} \) and \( l\text{sharelong} \), are consistent in terms of significance, magnitude, and direction across all four models, while coefficient estimates for the other variables fluctuate. Table 3 presents coefficient estimates and robust standard errors for all variables in all four models. In the following paragraphs I provide variable-by-variable analysis wherein I consider possible explanations for both the coefficient estimates themselves and any variation in the coefficients between the four models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled OLS</th>
<th>Pooled OLS</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{sharelong} )</td>
<td>-217.28*** (45.42)</td>
<td>-201.72*** (47.45)</td>
<td>-211.74** (101.21)</td>
<td>-191.25** (89.31)</td>
</tr>
<tr>
<td>( l\text{sharelong} )</td>
<td>0.0000415*** (7.06e-06)</td>
<td>-0.00446*** (0.0013)</td>
<td>-0.000029 (0.000023)</td>
<td>6.14e-07 (5.54e-06)</td>
</tr>
<tr>
<td>( \text{grant} )</td>
<td>0.00534*** (0.0013)</td>
<td>-0.00446*** (0.0013)</td>
<td>0.00319 (0.0020)</td>
<td>0.00111 (0.00199)</td>
</tr>
<tr>
<td>( \text{income} )</td>
<td>0.5707*** (0.0688)</td>
<td>0.6000*** (0.0701)</td>
<td>0.0736 (0.0945)</td>
<td>-0.0175 (0.0934)</td>
</tr>
<tr>
<td>( \text{rent1bdrm} )</td>
<td>-494.29*** (125.66)</td>
<td>-411.90*** (116.27)</td>
<td>319.88 (269.43)</td>
<td>524.10** (263.31)</td>
</tr>
<tr>
<td>( \text{ownshare} )</td>
<td>-347.63 (378.56)</td>
<td>39.48 (314.18)</td>
<td>161.33 (409.40)</td>
<td>120.05 (448.97)</td>
</tr>
<tr>
<td>( \text{poverty} )</td>
<td>356.67 (300.07)</td>
<td>568.86* (306.53)</td>
<td>84.33 (581.30)</td>
<td>-21.36 (594.86)</td>
</tr>
</tbody>
</table>

Table 3: Coefficient Estimates for Final Four Models.
<table>
<thead>
<tr>
<th></th>
<th>Pooled OLS</th>
<th>Pooled OLS</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>veteran</td>
<td>1068.28***</td>
<td>1159.52***</td>
<td>89.360</td>
<td>422.47</td>
</tr>
<tr>
<td></td>
<td>(197.03)</td>
<td>(195.72)</td>
<td>(540.44)</td>
<td>(643.37)</td>
</tr>
<tr>
<td>nonwhite</td>
<td>-134.63</td>
<td>-204.04**</td>
<td>392.32</td>
<td>296.04</td>
</tr>
<tr>
<td></td>
<td>(88.16)</td>
<td>(82.21)</td>
<td>(362.005)</td>
<td>(280.16)</td>
</tr>
<tr>
<td>population</td>
<td>0.00018***</td>
<td>0.00016***</td>
<td>0.00009</td>
<td>-0.00036</td>
</tr>
<tr>
<td></td>
<td>(.000029)</td>
<td>(.000022)</td>
<td>(.000050)</td>
<td>(.000050)</td>
</tr>
<tr>
<td>constant</td>
<td>202.71</td>
<td>12.71</td>
<td>-165.78</td>
<td>112.80</td>
</tr>
<tr>
<td></td>
<td>(166.80)</td>
<td>(139.04)</td>
<td>(427.69)</td>
<td>(489.55)</td>
</tr>
<tr>
<td>N</td>
<td>3,777</td>
<td>3,416</td>
<td>3,777</td>
<td>3,416</td>
</tr>
<tr>
<td>F-statistic</td>
<td>59.51***</td>
<td>58.51***</td>
<td>3.24***</td>
<td>2.96***</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.4897</td>
<td>0.5171</td>
<td>(overall) 0.2165</td>
<td>(overall) 0.3450</td>
</tr>
</tbody>
</table>

Estimates with robust standard errors in parentheses. *** indicates 99% level of confidence, ** 95% confidence, * 90% confidence.

Most notably for this analysis, the sharelong and lsharelong variables are significant in each of the four regressions at the 95 percent confidence level or above. In the pooled OLS model, sharelong is significant at the 99 percent level, suggesting that an increase in share of beds devoted to long-term interventions corresponds with a decrease in total number of chronically homeless individuals. Specifically, a ten percentage point increase in share of beds devoted to long-term services (or ten out of every 100 beds) is associated with a decrease of 21.7 total chronically homeless persons. Or, for every extra one bed out of 100 devoted to long-term services rather than emergency services, there will be an estimated two fewer chronically homeless persons.

The Fixed Effects model, taking into account time-invariant unobserved characteristics in each CoC that could influence the totalchronic variable, displays a similar result for this sharelong variable. In the FE model, a ten-percentage point increase in share of long-term beds corresponds with a 21.1-person decrease in the total count of the chronically homeless. This result is significant at the 95 percent level, and is nearly identical, numerically, to the estimate produced by the pooled OLS model.
The results for both pooled OLS and FE models using the lagged $isharelong$ variable follow a similar pattern. The pooled OLS model estimates that for each ten percentage point increase in share of long-term beds available in a given CoC, there will be 20.1 fewer chronically homeless persons counted in the following year. The FE model suggests that the same increase in share of long-term beds will correspond with a 19.1-person decrease in chronic homelessness in the next year. These results are significant at the 99 and 95 percent level, respectively.

Considering all four of these regressions together, the estimated relationship between share of total beds allocated to long-term services and total chronically homeless individuals in a CoC remains steady: a stronger devotion to long-term interventions over short-term interventions corresponds with a lower number of chronically homeless persons. These data suggest that converting one bed from short- to long-term service corresponds with an estimated two fewer chronically homeless individuals.

Other variables are less consistent across the four regressions. The $grant$ variable, a lagged measure of the total dollar amount of grant funds allocated by HUD to each CoC in the previous year, is significant in both pooled OLS regressions, but not the FE models. In each case the coefficient estimate is positive, suggesting that as grant funding increases by $100,000, total number of chronically homeless individuals increases by approximately four people. This would seem to indicate that grant funding causes more people to be homeless. However it is possible this counterintuitive relationship between funding and levels of chronic homelessness can be explained by a reverse causation effect. It is likely the $grant$ variable introduces a source of endogeneity into these regressions: grant funding is likely to go to CoCs that already have higher levels of chronic homelessness. The FE models correct for this endogeneity by controlling for
each CoC individually, and as a result, the *grant* variable is insignificant in each of the two FE models. This lack of significant coefficient for *grant* in both of the FE models suggests that after taking time-invariant CoC-specific unobservable factors into account, grant funding does not have an explanatory relationship with chronic homelessness. In other words, added grant funding does not successfully reduce (or increase) homelessness. I expand upon the implications of this idea in the Policy Recommendations section below. While the sign of this coefficient switches between the four models, the coefficient is so small in each case that this sign switch does not arouse much concern.

The coefficient estimates for the demographic and economic explanatory variables also fluctuate across the four models. The two pooled OLS models suggest that as median income in a CoC increases by $1,000, chronic homelessness decreases by between four and five individuals. However, estimates for this *income* variable are not significant in either FE model, suggesting there could be other unobserved factors specific to each CoC that account for this relationship, apart from income itself. The sign of the coefficients also switches from negative in the pooled OLS to positive in the FE, further suggesting the unobservable CoC-specific factors matter significantly.

The same is true for the *rent1bdrm* variable. The two pooled OLS models suggest that a $100 increase in monthly rent for a one-bedroom home corresponds with fifty-seven to sixty more chronically homeless people. While this relationship is consistent with the predictions of the theoretical model, the FE model produced no significant results for this variable, and a flipped sign for the FE model with the lagged *lsharelong* variable. Again, there are likely omitted variables in play that are accounted for when the FE tool is used, but not with pooled OLS.
Though the coefficient in the pooled OLS models seems high, and therefore important, the lack of significance in the FE models leads me to question the pooled OLS estimate for this rent variable.

The number of veterans as a portion of the population of the CoC follows a similar pattern as other demographic variables: significant in both OLS models but not in FE. The pooled OLS models suggest that as share of veterans in the population increases by ten percentage points, total number of chronically homeless individuals increases anywhere from 106 to 115 people. While this seems, again, to be a strong and stark relationship, it is once again likely that this variable introduces a source of endogeneity, further evidenced by the lack of significant result in the two FE models. It is likely that CoCs with more veterans, who are disproportionately represented in the homeless population, already have more chronically homeless individuals, and therefore the explanatory relationship disappears when CoC-specific effects are taken into account.

The relationship between home ownership rates and chronic homelessness is difficult to model in these regressions, as sign, significance, and magnitude all varied across the four models. The pooled OLS models suggest that total chronic homelessness count decreases by 4.1 to 4.9 people for every ten percentage point increase in homeownership rate. In contrast to the previous two demographic variables, this ownshare variable does have a significant relationship with totalchronic in one of the FE models, but in the reverse direction as the two pooled OLS models. In the FE model with the lagged lsharelong variable, an increase of ten percentage points in ownshare corresponds with an increase of 5.2 chronically homeless persons. Thus, after taking CoC-specific effects into account, the relationship between homeownership and
totalchronic changes direction. The insignificant coefficient on the non-lagged FE regression, however, remains positive. The inconsistency of this relationship is puzzling, and could be related to rapid changes in homeownership levels during and after the housing crisis, leading to high variance in homeownership rates, and making a relationship difficult to predict. Further research could be done to determine whether certain CoCs or years are driving this relationship, and whether those correspond with regions particularly hit during the financial crisis. There has also been increasing disagreement amongst housing economists and other scholars about whether homeownership remains as universally wise a financial choice as it has long been heralded.\footnote{Alfred M. Clark III connects the trends in homelessness in the United States with both the housing crisis and the resulting increased demand for rental housing, ultimately arguing that a proper response to the homelessness crisis is not encouraging homeownership but rather investing in expanding the stock of affordable rental housing (Clark, 2016). Similarly, Peter W. Salsich Jr. argues that even during the housing boom of the early 2000s, homelessness remained a serious problem (Salsich, 2011). Salsich’s comments suggest that overall increased homeownership may not have positive overall effect on the housing economy as we have long suspected.}

Racial and ethnic make-up, the nonwhite variable, is only significant in one of the models. The lagged pooled OLS model indicates that as nonwhite portion of the population increases by ten percentage points, count of chronically homeless individuals decreases by twenty people. While this result is significant at the 95 percent level of confidence, the t-statistics in the three other models are so low for this variable that I am unable to gain much insight from this one significant result. The sign also changes between the pooled OLS and FE models, from negative to positive, inserting another layer of ambiguity into the assessment.

This same conclusion holds for the unemployment rate, which is significant at the 90 percent level in only one regression: as unemployment rate increases by ten percentage points, total numbers of chronic homelessness increase by an estimated 56.8 people, according to the
lagged pooled OLS model. There are also vastly different magnitudes for the coefficients in the
four models, ranging from -21.36 to 568.86. Like the changes in homeownership rates during the
financial crisis, unemployment numbers varied widely as people entered and left the labor force
and went in and out of work, so it is possible the volatility of employment in this time period
contributes to the difficulty of modeling and understanding how this variable fits into the larger
picture of this analysis.

Poverty rate is an insignificant variable across models, also with broadly dissimilar
coefficients. I chose to keep this variable in the model, however, because it could help account
for effects of the financial crisis and other economic swings that may introduce bias into the
model. Since I do not include years, for reasons described in the sensitivity analysis below,
keeping poverty and other economic indicator variables in the model is important, though the
insignificant result seems to suggest that poverty rate of a CoC itself has no explanatory power in
impacting chronic homeless counts.

A possible explanation for the confusing coefficient estimates for poverty and uerate is
collinearity, as these two variables measure similar factors and could be closely correlated. A test
of collinearity revealed no such correlation, however, so I conducted further investigation by
running regressions with either poverty or uerate omitted. These models produced coefficient
estimates that were no different for both sharelong and lsharelong. Thus, I do not suspect the
inclusion of these two variables to bias the results for the main variables of interest.

Finally, population is significant only in the two pooled OLS models. As population of a
CoC increases by 100,000 people, total count of chronically homeless increases by sixteen to
eighteen people, according to these data. This relationship may be explained by the idea that
cities such as New York, Los Angeles, and Chicago have both high populations and high counts of chronically homeless individuals. Big cities also tend to have more services for the homeless, creating potential endogeneity or reverse causation concerns in the model. The FE model controls for these factors and corrects for the potential endogeneity, and therefore the explanatory relationship between population and total chronically homeless persons becomes insignificant. Though the FE with the lagged $lsharelong$ variable produces a negative coefficient for population, the size is so small that the sign change does not represent a large magnitude change (similar to the income variable above).

Taking all of these models and variables into account, particularly considering which variables are significant in each model, the FE models appear to be the most appropriate models with which to evaluate the effectiveness of long-term services in combating homelessness. Though F-statistics are significant at the 99 percent level in all four models, influence of CoC-specific fixed effects introduce bias into the pooled OLS models. In each case, demographic and economic indicators that appear to be significant in the pooled OLS models were no longer significant after unobservable time-invariant characteristics were accounted for. This suggests there is a stronger relationship between the CoC-specific characteristics and the specified demographic and economic indicators than there is between the total chronic variable and these demographic and economic indicators.

Because the $sharelong$ and $lsharelong$ variables are significant in all four models, and each of the four models is significant in and of itself, I can conclude with confidence that despite unobservable CoC-specific effects, there is a significant, negative relationship between share of beds devoted to long-term interventions and total numbers of chronically homeless individuals.
Thus, focus on long-term services does appear to be more effective in combating homelessness than reliance on emergency and other short-term interventions. Additionally, insignificance of the *grant* variable suggests that the type of service is more important to effectively ending homelessness than extra dollars spent on the effort.

I continue now with a detailed discussion of the sensitivity analysis I performed to further explore my results.
SENSITIVITY ANALYSIS

Due to a number of potential limitations in the data and models, I followed my initial regressions with a series of other tests to address such concerns. Outcomes from this sensitivity analysis further support the robustness of the results discussed in the previous section.

In each final regression, I do not control for year. When dummy variables for the years 2008 to 2016 are included in the FE models, using 2007 as the reference year, only one year emerges as significant (2011, significant at the 90 percent level). This lack of significance indicates to me that there is not enough variability year-to-year, with all other variables included, to warrant specifying controls for each year. When the year dummy variables are included, \( \text{sharelong} \) is still significant at the 90 percent level, with a coefficient of -196.65. This result is consistent with the regressions specified above, in terms of both magnitude and direction, so omission of the year variables does not lead to different conclusions. Similarly, the FE model using the \( \text{lsharelong} \) variable has no significant year dummy variables and produces a coefficient estimate of -173.36 for the \( \text{lsharelong} \) variable (significant at the 90 percent level). With these consistent results, I chose to leave the year variables out of the final models.

Second, I considered two separate data sets for each model prior to finalizing regression models. One set includes HIC and PIT data for all of the years between 2007 and 2016, and ACS data for 2007 to 2015, the only years for which data were available at the time of the analysis. For the second data set, I duplicated the observations for all ACS variables from 2015 to manufacture demographic and economic indicators for each CoC for 2016, so that the HIC and PIT data for 2016 (the key variables in the analysis) could be included. In an effort to understand whether this duplication is an accurate representation of 2016 demographic statistics, I analyzed
trends in a few key demographic variables: income, unemployment rate, population, and one-bedroom rent. In each case, I observed the trend and imputed an estimate for 2016, based on the trend. I then used the new variable in the same regression, and I observed identical results to the model with duplicated data instead of imputed data. Therefore, I concluded that a duplication of ACS data from 2015 to 2016 was an adequate method to estimate values for these demographic variables in my final data set. For my final four regressions, I use the second data set described above: the set with all years 2007 to 2016, using 2015 ACS data duplicated for 2016.

As an added layer of sensitivity analysis, I ran each model using the 2007 to 2015 data set, without manipulation to include the 2016 data. As the results in Table 4 indicate, coefficient estimates for key variables are still significant, using robust standard errors. While direction and significance remain consistent, magnitude varies more widely, both across these four models and in relation to the models with the 2007 to 2016 data. This change is perhaps not so surprising, given the smaller number of observations. Coefficient estimates for the sharelong and Isharelong variables for each of these four models using the 2007 to 2015 data are as follows. Only the years 2007 to 2015 are included, as the missing demographic variables for 2016 caused all 2016 observations to be dropped:

<table>
<thead>
<tr>
<th></th>
<th>Pooled OLS</th>
<th>Pooled OLS</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>sharelong</td>
<td>-177.99*** (48.87)</td>
<td>-225.45* (126.45)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Isharelong</td>
<td>-152.55*** (49.41)</td>
<td>-177.38* (100.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>3,390</td>
<td>3,029</td>
<td>3,390</td>
<td>3,029</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>55.73***</td>
<td>55.43***</td>
<td>1.90**</td>
<td>1.79*</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.4895</td>
<td>0.5193</td>
<td>(overall) 0.0068</td>
<td>(overall) 0.3920</td>
</tr>
</tbody>
</table>

Table 4: Coefficient Estimates, 2007 - 2015 data.

Estimates with robust standard errors ***indicates 99% level of confidence, **95%, *90%
Though F-statistics and R^2 values for the two pooled OLS regressions using the smaller dataset (2007 to 2015) are close to those with the larger data set (2007 to 2016), the F-statistics and R^2 values for the two FE models are poorer overall. Also, the range in the coefficient estimates (from -152 to -225) calls the reliability of these models into question, suggesting the results with the full, 2007 to 2016 data set better represent the true relationship between share of beds and count of chronically homeless individuals. The extra observations gained from the added year of data (2016) are necessary to gaining a better understanding of this relationship.

Because certain areas of the country have particularly high levels of chronic homelessness, I had some concern about outliers potentially skewing results. To investigate this potential concern, I conducted a grubbs test for outliers in the totalchronic variable. This test produced 143 outliers across the ten years of data. I removed these outliers and ran all four regression models again, without the outliers. Coefficient estimates for sharelong and lsharelong (reported in Table 5) remain significant, but with lower magnitude than in the models run with the full data set. I chose to keep those outliers in the full data set, however, because these CoCs labeled as outliers are also CoCs with large populations, which explains the high homeless population. This should not necessitate removal from the data set. Furthermore, these CoCs with such high homeless populations also tend to be those with more services available, so inclusion of these areas in the data set is critical for understanding how services relate to chronic homeless counts. I would thus miss critical information by leaving these data out of the analysis.
A final question I considered in putting together this analysis is the relationship between sharelong and the demographic and economic indicators included. My final four models suggest that after accounting for CoC-specific fixed effects, these demographic and economic indicators have no explanatory power in determining total number of chronically homeless individuals. In other words, poverty rate, racial make up, unemployment rate, population, and other such characteristics of a CoC cannot be used to predict how many chronically homeless people a given CoC will have. Can these variables, however, be used to predict the services to combat homelessness available in each CoC? Or, is there a statistically significant relationship between these demographic variables and the sharelong variable? Table 6 shows the coefficient estimates for a fixed effects model with sharelong as the dependent variable and the same demographic and economic indicator variables as the independent variables.

<table>
<thead>
<tr>
<th>Table 5: Results Omitting Outliers.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>sharelong</strong></td>
</tr>
<tr>
<td><strong>sharelong</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
</tr>
<tr>
<td><strong>F-Statistic</strong></td>
</tr>
<tr>
<td><strong>R²</strong></td>
</tr>
</tbody>
</table>

Estimates with robust standard errors in parentheses ***indicates 99% level of confidence, **95% confidence, *90% confidence.
Table 6: Coefficient Estimates with *sharelong* as Dependent Variable.

<table>
<thead>
<tr>
<th></th>
<th>Coefficient (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>income</em></td>
<td>5.97e-06*** (1.05e-06)</td>
</tr>
<tr>
<td><em>rent1bdrm</em></td>
<td>0.00017*** (0.000054)</td>
</tr>
<tr>
<td><em>ownshare</em></td>
<td>-1.067*** (0.1428)</td>
</tr>
<tr>
<td><em>veteran</em></td>
<td>-2.402*** (0.2904)</td>
</tr>
<tr>
<td><em>poverty</em></td>
<td>0.5461*** (0.1553)</td>
</tr>
<tr>
<td><em>nonwhite</em></td>
<td>-0.0344 (0.1262)</td>
</tr>
<tr>
<td><em>population</em></td>
<td>1.96e-07*** (6.69e-08)</td>
</tr>
<tr>
<td><em>uerrate</em></td>
<td>-0.5363*** (0.1081)</td>
</tr>
<tr>
<td><em>constant</em></td>
<td>0.6732*** (0.1402)</td>
</tr>
<tr>
<td>N</td>
<td>3,871</td>
</tr>
<tr>
<td>F-statistic</td>
<td>85.33***</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0347 (overall)</td>
</tr>
</tbody>
</table>

Estimates with robust standard errors in parentheses ***indicates 99% level of confidence, **95% confidence, *90% confidence.

As these results indicate, there seems to be a significant relationship between demographic and economic characteristics of a CoC and the propensity of that CoC to use long-term interventions. According to these data, as median income of a CoC increases by $10,000, the share of long-term interventions increases by an estimated 5.97 percentage points. As homeownership rate increases by ten percentage points, share of long-term beds decreases by about ten percentage points. A 100,000-person increase in population corresponds to an increase of approximately two percentage points in share beds allocated for long-term services. As unemployment rate increases by ten percentage points, share of long-term beds decreases by an estimated 5.3 percentage points. These estimated effects of demographic shifts on share of long-
term beds are not large, but they are clear, significant relationships, indicating predictive power for each of these characteristics. Generally, as income, area rents, poverty rate, and population increase, share of long-term beds also increases. As homeownership rate, veteran population, minority population, and unemployment rate increase, share of long-term beds decreases. These are all relatively instinctive results, with the exception of unemployment rate, but the general volatility and fluctuation of unemployment rates could help explain this counterintuitive result.

Taking these results further, I wanted to learn if these demographic and economic indicators alone hold statistically significant relationships with total chronic homeless counts, without sharelong specified in the model. A FE model with totalchronic as the dependent variable and these demographic indicators as independent variables, without sharelong included, produces only one significant coefficient: ownshare. This result suggests to me that these demographic and economic characteristics, while predictive of sharelong, cannot replace sharelong in the model.

This added layer of analysis allows me to state more definitively that the share of long-term beds is the strongest predictor of the count of total chronically homeless individuals, leading to a robust conclusion that long-term interventions have a statistically significant impact on chronic homelessness, even after controlling for a number of other factors, including grant funding.

I turn now, finally, to a discussion of the policy implication of these results.
POLICY IMPLICATIONS AND RECOMMENDATIONS

The purpose of this study was to evaluate the effectiveness of permanent, long-term interventions to combat homelessness as compared to time-limited, short-term services. Existing research speaks to the effectiveness of specific types of long-term interventions in serving certain subpopulations, such as people living with mental illness or veterans, but not the wider population of the chronically homeless as a whole. Similarly, existing evaluations are confined to anecdotal and theoretical grounding for effectiveness of permanent, low-barrier solutions to homelessness, while this study sought to determine whether quantitative evidence supports the qualitative.

I hypothesized that a larger number of long-term services, as a share of all services available, would result in lower numbers of chronically homeless individuals. Results support this hypothesis: higher shares of services allocated to long-term interventions correlate with lower counts of chronic homelessness, both in the current year and in the following year. On average, as the share of long-term beds available increases by ten percentage points, total count of chronic homelessness decreases by nineteen to twenty-one people, depending upon the model. In other words, every one out of 100 beds converted from short- to long-term, leads to two fewer chronically homeless people. These results remain consistent after controlling for various demographic and economic indicators, level of HUD grant funding provided to the region, and region-specific unobserved fixed effects.

The main policy implication of this result is straightforward: organizations working to combat homelessness should transition away from emergency, short-term interventions toward permanent, comprehensive services that offer non-time-limited support and stability. There is
already a trend in this direction, so service-providers should lean in to this momentum and focus on improving these long-term modes of intervention. Continuums of Care could accelerate this shift by offering training and other resources to organizations seeking to make the transition to permanent interventions, which necessitate significant startup costs.\(^w\)

There were seventy-eight CoCs in 2016 with twenty or fewer chronically homeless people. If these seventy-eight jurisdictions add as many as ten long-term beds to their portfolio (or convert ten transitional housing units to permanent housing units), they could completely eliminate chronic homelessness. As cities across the nation seek to engage in the Mayors Challenge to End Homelessness, incorporating strategies of long-term, holistic care will go further in pursuing the goal of eliminating chronic and veteran homelessness than traditional transitional services.\(^x\) The CoC structure already invites collaboration between regional governments, and this paper’s evidence provides rationale for the best service model to use moving forward. Mayors have the power to add local funds to existing HUD grants to expand the offering of long-term services, and this paper’s evidence justifies such spending.

\(^w\) Not many comprehensive reviews of the cost-effectiveness of Permanent Supportive Housing exist at the point of this study, but the few that have been published speak to notable cost savings when transitioning from emergency housing to PSH models (Ly & Latimer, 2015). A 2015 study of the savings and offsets associated with placing homeless seniors in PSH reported significant savings, particularly in healthcare costs (Bamberger & Dobbins, 2015). More anecdotal evidence suggests PSH will lead to reduced spending on emergency medical care, incarceration, emergency psychiatric care, temporary shelter costs, and other public expenses currently used to care for the homeless population. This suggests that though PSH and other permanent interventions have large start-up costs, they could be more cost-efficient in the long run.

\(^x\) The Mayor’s Challenge is an initiative begun in 2014 by the U.S. Interagency Council on Homelessness to provide resources and motivation for cities across the country to eliminate Veteran Homelessness in their borders. Since 2014, 880 mayors have signed on, and 37 cities and 3 states have eliminated veteran homelessness (Mayor’s Challenge to End Veteran Homelessness (2017)).
Despite this evidence, I would not advocate for eliminating emergency housing entirely, as a need certainly persists for emergency shelter to provide short-term relief from homelessness. Emergency, transitional, and Safe Haven beds are necessary and important for serving communities with those specialized needs. Instead of eliminating short-term housing services, CoCs should consider how services are allocated between these traditionally dominant short-term models and new longer-term ones. Any new beds or new resources that are added to the service portfolio at the CoC should be allocated for long-term interventions such as Rapid Re-Housing, Permanent Supportive Housing, and other evidence-based permanent housing interventions. Data indicate total services are expanding nationwide, so it would be prudent to ensure these added services are the most efficient type: non-time-limited.

Simultaneously, there is need for new research on the effectiveness of each of these long-term programs for consumers of different types: individuals, families, veterans, people with mental illness or physical disabilities, and others. As these long-term programs become more widespread, service-providers can tailor them to be as effective as possible for each population. As CoCs expand understanding of the demographics and characteristics of the homeless population in their regions, they can more accurately determine what type of permanent intervention works best. As service providers specialize their own service models, a comprehensive coordinated system of service-allocation can help ensure that each individual and family experiencing homelessness receives exactly the kind of support it needs.\(^\text{y}\)

\(^\text{y}\) An excellent example of this type of coordinated care system is Coordinated Entry in Washington, D.C. This program is designed to quickly and efficiently place people experiencing homelessness into housing, according to each individual’s level of need. When someone experiencing homelessness enters the system, he or she undergoes an assessment about his or her level of need, and he or she is placed in the services of a housing provider specialized to those
Though the influence of grant funding in each CoC proved to be an insignificant factor in determining levels of chronic homelessness in this study, this insignificant result still has important policy implications. The insignificance of the grant variable suggests that merely throwing money at the problem of homelessness is not the solution. Rather, efficient spending of current levels of funding has larger impact. This interpretation of the data may seem discouraging for advocates of increased funding for homelessness programs, but it need not be. While homeless services are chronically underfunded, this evidence suggests that progress can be made with limited resources, if those resources are utilized efficiently. A key policy takeaway from these data is that the solution to ending homelessness is not more money, but rather money spent more effectively.

A final implication of this research is the lack of significance of the other demographic and control variables. I expected correlation between economic factors such as poverty rate and unemployment rate and levels of chronic homelessness. But these variables were all insignificant in the FE regressions, suggesting the economic conditions in the CoC are not useful indicators of chronic homelessness numbers. Similarly, demographic factors such as population of color and veteran population, and size of the CoC itself were also not significant predictors of chronic homelessness levels. The only significant factor in each regression was the share of long-term beds available. Demographic and economic indicators, then, cannot predict and do not affect how many people are homeless. Service provision, something that is controllable and relatively easily adjusted (unlike demographic and economic factors), does have significant impact on needs. This ensures every person receives the support he or she requires as quickly as possible and that no duplication or overlap of services occurs. Such a program is efficient, resource-conscious, and sustainable. (D.C. Coordinated Entry (n.d.))
ending homelessness. Again, the implication here is that the only factor in these models that significantly correlates with lower counts of homelessness is the tangible, adjustable factor: service-type. This again provides promising evidence that actions matter. Combating chronic homelessness does not require certain environmental conditions, but rather the appropriate service action.

This study merely scratches the surface of the potential insights we can gain from HIC and PIT data. I would be interested in future research on the relationship between chronic homelessness and long-term services with more of a lag involved, for example. This would allow us to better understand whether these services have the intended consequences over more time. Such an analysis will become possible in the years to come, as data are collected annually, providing a wider base of observations to draw upon.

Furthermore, there are a number of cities and programs that have engaged in specific campaigns to combat homelessness, allocating dedicated resources above and beyond the standard amount for short durations. A prudent research project would be to create a variable for these specialized campaigns to see if they have the intended added effect in reducing chronic homelessness numbers. Does this “blitz” effort actually work in permanently transitioning people out of homelessness? And should more communities adopt such a strategy?

Additionally, it would be helpful to have a better understanding of how different types of interventions function in different environments. For example, does transitional housing function better in a suburban area full of families who only need temporary relief rather than long-term

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² Though the variables discussed above likely correlate with short-term homelessness, the focus of this study is chronic homelessness. Thus these data provide no evidence for correlation between demographic and economic indicators and chronic homelessness.
stabilization? Does Rapid Re-Housing function best in a rural place where housing is easier to afford but harder to find? Do different types of markets and populations create environments where certain types of programs work more or less effectively? This type of analysis would require more nuanced HIC and PIT data, and perhaps ACS data broken down to more granular levels, but any future study on further improving the efficacy of services to combat homelessness would benefit from a more nuanced understanding of what programs are effective in which environments.

Finally, I am interested in how broader housing policy impacts homelessness. Including availability of Public Housing and Housing Choice Vouchers, the two major forms of federal housing assistance, in the models would help paint a more comprehensive picture of the connections between affordability in housing and levels of homelessness. As a result, policymakers could leverage tools of federal housing policy as well as localized service models to even more efficiently target scarce funding and therefore have the strongest impact on reducing and eventually eliminating homelessness.
CONCLUSION

In this study, I used national level panel data to conduct a quantitative evaluation of different types of services designed to combat homelessness. I categorized services into two groups—short-term and long-term—and used both pooled OLS and Fixed Effects regression models to estimate the relationship between share of total services devoted to long-term support and total counts of chronically homeless individuals on the CoC level. I hypothesized, based upon existing research, that a higher share of long-term interventions would correspond to lower counts of chronic homelessness.

All four models were statistically significant at the 99 percent level, and produced statistically significant coefficient estimates for the key independent variables of interest: share of long-term beds and a one-year lagged measure of share of long-term beds. The data show that a ten percentage point increase in the share of beds devoted to long-term services corresponds with twenty fewer chronically homeless people, suggesting that long-term interventions are more effective in combating chronic homelessness than time-limited ones. Moving forward, CoCs and the governments within should invest resources in Permanent Supportive Housing and other permanent housing programs to most efficiently and effectively help the 77,000 chronically homeless individuals across the United States today transition out of homelessness indefinitely.


