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Predicting Client Housing Outcomes from Georgia's Homeless Management Information System with Hierarchical Generalized Linear Modeling

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PREDICTING CLIENT HOUSING OUTCOMES FROM GEORGIA'S HOMELESS MANAGEMENT INFORMATION SYSTEM WITH HIERARCHICAL GENERALIZED LINEAR MODELING

by

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Author's Statement Page

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Abstract

During a given night in the United States, approximately 553,742 people experience homelessness, and 1.4 million people stay in an emergency shelter or transitional housing program each year. The aim of this study is to use a multilevel modeling approach to examine which client level and program level factors are associated with achieving permanent housing at program exit, as few studies in current literature assess both client and programmatic factor impact on housing outcomes simultaneously. Client level data from Georgia's Homeless Management Information System for 8,756 clients enrolled in housing assistance programs was analyzed. The average age was 42.05; 71.96% of clients identified as Black or African American, 57.15% were male, 31.41% had mental illness, and 83.65% were in households without children. Data was analyzed using hierarchical generalized linear modeling to estimate the log odds of successful placement in permanent housing considering both client and program characteristics. Results show that individuals who were male, in households without children, and had mental illness were less likely to obtain permanent housing at program exit, regardless of which type of housing assistance program they were enrolled in. Clients enrolled in programs within the City of Atlanta were just as likely to obtain permanent housing at program exit as clients enrolled in programs outside of the city. Households with children were better able to secure permanent housing upon the conclusion of their housing assistance, controlling for program type and other client level factors. Clients who had been homeless for one year or longer prior to entering a housing program were less likely to obtain permanent housing at program exit. Findings indicate that more research on the barriers to housing for individuals in households without children is needed in order deliver appropriate and effective support services. This also implies that we need more support for single homeless men and those who have been homeless previously to help them achieve permanent housing.

Key words: homelessness, housing outcomes, HMIS, hierarchical generalized linear modeling

Introduction

During a given night in the United States, approximately 553,742 people experience homelessness, and 1.4 million people stay in an emergency shelter or transitional housing program each year (Henry, Watt, Rosenthal, & Shivji, 2017; National Alliance to End Homelessness (NAEH), 2016a). According to the U.S. Department of Housing and Urban Development (HUD), homelessness is defined as the lack of a fixed, regular, or adequate place to reside during the night. Studies have shown that homelessness impacts personal well-being, mental health, physical health, and mortality, emphasizing the importance of immediate permanent housing solutions in minimizing the lasting impact homelessness can have on someone's life (Henry, Watt, Rosenthal, & Shivji, 2017; Geddes & Fazel, 2011). Housing instability and homelessness are caused by a multitude of factors, from simply a lack of affordable housing, to domestic violence, to disabilities and mental illness (NAEH, 2016b). Since the Homeless Emergency Assistance and Rapid Transit to Housing (HEARTH) Act was passed in 2009, the organization responsible for addressing homelessness, HUD, has been encouraging community-wide organized efforts to assess the needs of homeless individuals and families and to provide necessary services in a more coordinated, effective, and efficient manner (NAEH, 2016c). Rates of homelessness throughout the United States have been declining in recent years, partially because of improvements in housing assistance, an increase in the utilization of best practices such as Housing First, and improvements in the American economy in years since the recession (NAEH, 2016d).

There are 4 main types of housing interventions that are used to address homelessness in the U.S. Emergency shelter (ES) is simply a temporary shelter for people experiencing homelessness which usually lasts less than 90 days. Transitional housing (TH) programs provide both shelter and some supportive services for people experiencing homelessness, but again this is temporary housing lasting no longer than 24 months. Rapid Rehousing (RRH) is the newest housing intervention to be implemented in the U.S. The program is designed to provide temporary housing assistance to individuals and families experiencing homelessness and quickly transitioning them into permanent housing. This assistance can last anywhere from a couple of months to a year (Henry, Watt, Rosenthal, & Shivji, 2017). Permanent Supportive Housing (PSH) is a long term housing option for persons who are homeless living with a disability. In this program, clients must have a disability to be eligible and they are provided with housing and supportive services for as long as they wish to continue participating in the program. Clients enrolled in PSH can stay enrolled for as long as they like, whereas ES, TH, and RRH all do have time limits on the assistance available. These housing intervention types have the same general purpose, to provide housing assistance, but they each play a unique role in the homeless service system. Permanent, affordable housing options are the solution to homelessness, and it is important to understand how the homeless service system can quickly and efficiently connect people with the most appropriate permanent housing for each person's circumstances (NAEH, 2016a).

The number of RRH programs throughout the nation and increases in the availability of PSH programs have provided more permanent housing opportunities for those who find themselves experiencing homelessness than in the past. The capacities of two housing program types in particular, PSH and RRH, have grown 69% and 204%, respectively, in the last four years alone (NAEH, 2016d). This is partly due to HUDs shift in funding from TH programs to focus funding on RRH programs because of the HEARTH Act's emphasis on RRH and PSH. In addition to these changes, a policy that HUD has been advocating for more recently called

Housing First, which aims to connect people experiencing homelessness to permanent housing quickly and without barriers to entering the homeless service system such as sobriety, service participation, employment requirements, and the like, is helping to increase the number of people who can access homeless services (HUD, 2013). Through Housing First, housing stability is maximized by eliminating barriers to accessing resources, providing supportive services, and empowering clients by self-determination.

Homelessness is more recently thought to be a public health issue as this field has discovered how closely health and homelessness are related. Negative physical and mental health outcomes are associated with homelessness, which can be especially true in counties with poorly organized welfare systems (Fazel, Geddes, & Kushel, 2014). People who experience homelessness have higher rates of premature mortality than the rest of the population, due to suicide and other mental illness, infectious diseases, and substance abuse. They also tend to have poorly managed non-communicable or chronic diseases such as cardiovascular disease, diabetes, and hypertension. The homeless population often has difficulty accessing medical care and thus utilizes emergency departments as their primary access point for medical care (Fazel, Geddes, & Kushel, 2014; Moore, Gerdtz, & Manias, 2007). One study indicated that the homeless population comprised 10% of all emergency department visits (Moore, et al., 2012). This is an incredibly expensive way to access healthcare. In fact, the utilization of publically funded crisis services such as emergency departments, detox programs, psychiatric facilities, and jails costs tax payers in the United States $35,578 per year for every chronically homeless individual (NAEH, 2015). Providing low barrier, permanent housing solutions for homeless would greatly reduce that cost burden, and it would also greatly improve the health of those individuals.

Experiencing homelessness is extraordinarily stressful and can have a long lasting impact on one's life. Children who experienced homelessness have increased rates of behavioral issues and mental disorders compared to their peers (Morris & Strong, 2004). Adults experience high levels of stress, social isolation, and poverty. Parents find it difficult to obtain healthcare and their children's school attendance declines (Morris & Strong, 2004). They face bureaucratic, social, and financial barriers to accessing services. Due to the impact that homelessness can have on individuals and families, the faster that people transition from homelessness into a permanent housing option, the less severe the impact of the episode of homelessness will have on that individual or family.

Given that so many Americans experience homelessness each year, and the great impact that an episode of homelessness can have on an individual, it is imperative that instances of homelessness are a brief, rare, and do not reoccur once someone has been placed in permanent housing. In order to understand the most effective ways to address homelessness, researchers must continue to identify characteristics that may predispose an individual of family for homelessness and ensure that services are in place to provide support and stop homelessness for occurring in the first place, as well as investigate how to most swiftly and accurately assist those experiencing homelessness with finding permanent housing options. However, each community faces its own unique obstacles as each community, as well as the housing programs and clients in it, has its own characteristics. Because of this and the varying circumstances that lead households experiencing homelessness to become homeless, it is necessary that when evaluating client housing outcomes, researchers examine not only client level factors but programmatic factors as well to get a more comprehensive view of the factors contributing to the outcome.

The purpose of this study is to examine the relationship between client level and programmatic factors in order to estimate the odds of successfully exiting homelessness. Demographic factors are assessed to determine the contribution that they make to housing outcomes, while controlling for housing intervention type and other known variants related to homelessness. Location of the housing intervention, as well as family type and length of time spent in previous periods of homelessness are also evaluated to establish their relationship with housing outcomes.

Literature Review

There is a limited body of literature focused on homelessness, and more specifically focused on housing outcomes for those who experience homelessness. This literature review will first cover characteristics in the literature that have been found related to homelessness or have a higher prevalence in the homeless population that in the general population. Then I will highlight studies that have concentrated on evaluating housing outcomes among those who have fallen into homelessness as well as those who have employed Hierarchical Linear Modeling in homeless service system research. Lastly, I will comment on the gaps in the current literature and the importance of the present study in helping to contribute to a more thorough understanding of this topic.

Although the homeless population is described as a heterogeneous population, there are certainly patterns in the data highlighting common characteristics. Drug and alcohol use and abuse have long been cited as a factor closely related to homelessness (Fazel, Geddes, & Kushel, 2014). TO and colleagues (2016) found that male gender and drug use were associated with experiencing homelessness. Among female welfare recipients, mental and physical health problems, criminal conviction, domestic violence, illicit drug use, and having less than a high school education were associated with homelessness (Phinney, Danziger, Pollack, and Seefeldt, 2007). Research indicates that veteran status, income, housing intervention type, gender, substance use history are predictors of homelessness as well as returns to homelessness upon program discharge (Brown, Vaclavik, Watson, and Wilka, 2017; To et. al., 2016). Research shows that substance abuse disorders are also associated with recurring episodes of homelessness (McQuistion, Gorroochurn, Hsu, and Caton, 2014).

Another factor that is closely tied to homelessness is mental illness. During the 2015 Point in Time Homeless Count, 13% of the homeless population in Georgia self-identified as having a mental illness, although national statistics for that year state that 24% of the homeless population in the United States were considered severely mentally (Georgia Department of Community Affairs, 2015;U.S. Department of Housing and Urban Development, 2015). Researchers point to mental illness as a precursor for becoming homeless (Thompson, et al., 2010). Research also suggests that mental illness perpetuates homelessness by creating barriers to employment as well as barriers to accessing services (Poremski, Whitley, & Latimer, 2014; Hwang & Burns, 2014). Mental illness often co-occurs with substance abuse and misuse in this population (Hwang & Burns, 2014). Studies estimate between 10 and 20% of the homeless population experience both mental illness and substance abuse (Moore, Gerdtz, & Manias, 2007) The combination of mental illness and substance abuse makes it challenging to access housing services as programs have sobriety and behavioral requirements that may be easily violated by mentally ill drug abusers who are not receiving treatment, creating another barrier to obtaining necessary services to exit homelessness (Hwang & Burns, 2014). The Housing First approach involves a low barrier admission criteria for housing program entry, which enables program participants to be housed first and then address the underlying issues that may have caused or perpetuated their homeless experience such as mental illness and substance abuse (Watson, et al., 2017). This is a philosophy that greatly impacts the characteristics of the programs that abide by it, which is why program characteristics should be taken into consideration when evaluating client outcomes in this area of research.

Research has also shown that prior episodes of homelessness are a risk factor for episodes of homelessness in the future (O'Connell, Kasprow, & Rosenheck, 2008). Long term homelessness can be detrimental to the health and wellbeing of those who experience it. Sixteen percent of the homeless population is classified as chronically homeless during the most recent point in time homeless count in 2017. Those who are considered chronically homeless have a disability and been homeless for a year or longer or have been homeless on more than four occasions in the past three years with all those occasions adding up to a year or longer (Henry, Watt, Rosenthal, & Shivji. 2017). This population poses its own particular challenges as those who are chronically homeless are more vulnerable and tend to utilize a significant portion of public services, while unable to attain housing stability (Caton, Wilkins, & Anderson, 2007). Older age, criminal history, poor coping skills, lack of earned income or employment, inadequate family support, and history of substance abuse are all predictors of long term homelessness (Caton et al., 2005).

Previous literature links race to risk of homelessness. Given that African Americans have higher prevalence rates for poverty than white Americans, it is unsurprising that 41% of those experiencing homelessness in the U.S. in January of 2016 were African American when only 13% of the U.S. population is black (Henry, Watt, Rosenthal, & Shivji, 2017; U.S. Census Bureau, 2016a). A study done in 2018 in a sample of several U.S. cities found that 64.7% of people experiencing homelessness were Black, while only 28.0% were White (Olivet et al., 2018). .African Americans are more likely to develop chronic health problems, meaning that the black homeless population is particularly vulnerable to premature death (Jones, 2016). Black veterans have been found more likely to experience homelessness than white veterans, and black adults experiencing homelessness have higher rates of drug abuse and childhood adversity than their white counterparts (Jones, 2016). There are racial differences in service outcomes that should be taken into consideration when studying or addressing homelessness.

Another factor to consider is age; the homeless population is beginning to age as the generation of baby boomers ages and faces challenging economic and social circumstances such as deindustrialization and reduced welfare subsidies (Culhane, et al.,2013). While HUD has recently be emphasizing the need for services specifically for homeless youth, ages 18 to 24, who have more life stressors, these individuals spend less time homeless and have fewer physical symptoms than the older adult homeless population (Tompsett, Fowler, & Toro, 2009). In the 2017 point in time count, 61% of the overall homeless population in the U.S. were men; however 71% of the unsheltered homeless population were men, indicating that men are less likely to access shelter services (Henry, Watt, Rosenthal, & Shivji. (2017). This is reflected in other research which indicates that homeless men had difficulty asking for help when needed and more often struggle with alcohol and substance abuse (Amato & MacDonald, 2011). These subpopulations of age, race, and gender experience homelessness differently, and these factors do contribute to an individual's ability to exit homelessness.

In recent years HUD has challenged communities across the U.S. to end veteran homelessness, and rates of veteran homelessness have declined. In 2010, there were just over 74,000 homeless veterans on a given night in the U.S., making up approximately 11% of the homeless population. In 2017, about nine percent of all homeless adults in the U.S. (Henry, Watt, Rosenthal, & Shivji. (2017). However, of the U.S. population, only about seven and a half percent are veterans, meaning that veterans are experiencing disproportionately high rates of homelessness (U.S. Census Bureau, 2016b). Studies have shown that posttraumatic stress disorder along with other mental health factors and socioeconomic factors are significant risk factors for homelessness that are particularly prevalent for veterans (Metraux, Clegg, Daigh, Culhane, & Kane, 2013; Tsai & Roseheck, 2015). Research also indicates that veteran status is a predictor of reentry into homelessness after permanent housing placement (Brown, Vaclavik, Watson, and Wilka, 2017). Veterans are more susceptible to homelessness than other citizens in the U.S. population.

Another subpopulation that has a large presence within the homeless population is single individuals or other households without children. According to the census, in 2012, 66% of households in the United States were family households with children (Vespa, Lewis, & Kreider, 2013); however, in 2017, 67% of the homeless in the U.S. were individuals in households without children (Henry, Watt, Rosenthal, & Shivji. 2017). These individuals are more likely than families with children to be unsheltered homeless, meaning that they are more likely to live in a place not fit for human habitation such as a park bench, a car, or an outdoor encampment (Henry, Watt, Rosenthal, & Shivji. 2017). Multiple sources site a simple lack of affordable housing as the cause for homelessness among this population (NAEH, 2017; Routhier, 2016). With a single income households, more employment and support services may be needed to successfully exit homelessness (NAEH, 2017).

Having low or limited income is the most cited reason households experience homelessness. Individuals and families may have low income because of lack of education or training, criminal history, unreliable transportation, health problems, or unstable housing, among other issues (NAEH, n.d.). Once homeless, finding employment is a barrier to that must be overcome in order to find housing. One major obstacle is that affordable housing is hard to come by and is increasingly difficult to secure. Since 2007, the number of households who are considered severely cost burdened, are paying more than 50 percent of their income towards housing, increased by 28 percent (NAEH, 2016d). Affordable housing fell by 60 percent in just 6 years, between 2010 and 2016. Income has remained stagnant as housing costs have increased, making obtaining affordable housing seemingly impossible to obtain (Freddie Mac, 2017). Employment training is offered along with housing interventions inconsistently throughout Georgia, thus income is another factor to consider when examining exits from homelessness.

A significant amount of research on homelessness is restricted to the examination of urban homeless populations. This hinders the ability of policy makers to address homelessness in a rural or suburban setting. Homelessness looks very different in rural and suburban communities than it does in urban communities (NAEH, 2010). Transportation methods, employment opportunities, housing availability, and medical and social services can be more spread out and difficult to obtain in these settings. The infrastructure needed to address homelessness and provide housing services is often lacking in rural areas (NAEH, 2010). To date there are few if any studies comparing housing assistance program outcomes between rural, suburban, and urban settings. These types of studies are needed to determine how to address homelessness in each of the settings as what is needed to address homelessness in New York City may look different from what is needed to address homelessness in rural Alabama or suburban Minnesota. The data analyzed in the study encompasses urban, suburban, and rural homeless populations in Georgia, and with thus, contribute to the current body of work in this area.

The more aware researcher are of the factors associated with homelessness, the better the homeless services system can provide services to prevent homelessness from occurring in the first place or recurring for those who have already experienced it. While there is certainly empirical and practical value in knowing what the risk factors and protective factors are for becoming homeless, it is also important to examine which factors impact one's ability to exit homelessness in order to address homelessness once it happens. Previous research on homelessness has featured longitudinal methods (Aubry, et al., 2016; To, et al., 2016; McQuistion et al., 2014) or Kaplan-Meier survival curves (Brown, Vaclavik, Watson, & Wilka, 2017); however HLM has not been used to examine client level and program level factors simultaneously to examine housing outcomes, despite the fact that the structure of Homeless Management Information System data lends itself well to this type of analysis.

The Homeless Management Information System (HMIS) is an information technology system used to collect client-level data regarding homeless individuals and families and persons at risk of homelessness who access homeless services (HUD, 2017). It is used to examine system usage, report demographics and evaluate basic community performance which is communicated from communities to the U.S. Department of Housing and Urban Development through various reports (HUD, 2017). The reports include the Annual Homeless Assessment Report, Annual Performance Report, Point in Time Count, Consolidated Annual Performance and Evaluation Report, and System Performance Measures. These reports are submitted by all communities who receive various federal grants from HUD, but published research using HMIS data is limited.

The Family Options Study used HMIS data to compare the efficacy of Rapid Rehousing to other intervention types (Gubits, et al., 2016). One study examined risk of return to homeless services among permanently and nonpermanently housed single adults in Indianapolis, Indiana (Brown, Vaclavik, Watson, & Wilka, 2017). One study using HMIS examined the patterns of families' involvement with homeless shelters and child protective services in Alameda County, California (Rodriguez, & Shinn, 2016). Another study examining returns to homelessness for those exiting Rapid Rehousing and Transitional Housing interventions using HMIS data (Rodriguez & Eidelman (2017). There are simply not very many peer reviewed, published studies I have found that have utilized this HMIS data, let alone used it to evaluate housing outcomes for those who are accessing housing assistance services. This lack of published research could be because there are communities use their data to inform local policy and don't usually share it outside of the immediate homeless service community. HMIS data is not publically available; in order to conduct research using HMIS, researchers would have request the data from that community or communities in order to use it (HUD, 2017).

Because homelessness is caused by myriad factors and is addressed in varying ways depending on resource availability, program type and location, among other things, it's crucial that when examining and evaluating the effectiveness of these housing interventions, both client level and program level factors are considered. Much of the research in this subject area focuses on one type of housing intervention per study, the many of which are emergency shelters (Aubry, et a., 2016; McQuistion et al., 2014). The Family Options Study comparing the efficacy of Rapid Rehousing to other intervention types is one of a few exceptions, along with research by Rodriguez and Eidelman in 2017, although the Family Options Study was focused exclusively on households with children (Gubits, et al., 2016). This study was extensive, including 2,282 families from shelters in 12 communities across the United States. These families were randomly assigned to 4 housing conditions: a permanent housing subsidy with no supportive services attached and no time limit, a transitional housing project with temporary rental assistance for up to 24 months with onsite, intensive support services, a rapid rehousing project with up to 18 month of rental assistance and housing focused support services, and usual care or any other housing that a family accessed without a referral (Gubits, et al., 2016). These families were followed for 3 year after assignment; findings suggest that families who receive subsidies has a reduction in subsequent shelter stays, and that RRH is more cost effective than usual care

(Gubits, et al., 2016). Because the homeless service system does have varying housing options to meet the varying needs of those experiencing homelessness, and because clients can use more than one type of housing intervention, it's important that factors related to exiting homelessness are examined while accounting for intervention types.

It is clear that an inability to obtaining stable, permanent housing has a great impact on the lives of those who experience homelessness from mental, physical, and social health perspectives. Families who experience housing instability risk hindering cognitive and developmental growth in their children (Fowler, et al., 2015). Failure to exit homelessness leads to poor personal well-being and life satisfaction (Johnstone, et al., 2016). However, communities who increase their PSH capacity have observed decreases in their subsequent homeless counts (Corinth, 2017), indicating that PSH is effectively cultivating housing stability for those clients enrolled in the programs. PSH interventions show not only an increase in housing stability and behavioral health outcomes, but also increased access to healthcare and improved health outcomes in the most vulnerable among the homeless (Henwood, et al., 2013). RRH and the adoption of the Housing First model is having a positive impact on communities and leading to high rates of permanent housing placement, increased self-sufficiency, and fewer returns to homelessness (NAEH, 2014). Examining the factors that impact an individual or family's ability to exit homelessness by obtaining permanent housing can assist the homeless service community in building best practices and policies from a place that is data driven and evidence based. This is especially important with regard to HMIS data as this is the data that is collected for this population across the U.S., and should be used as a tool to ensure that those who have the unfortunate experience of falling into homelessness can be helped out most swiftly and effectively while minimizing lasting impact.

The aim of this study is to use a hierarchical linear modeling (HLM) approach to examine which client level and program level factors are associated with leaving homelessness in the state of Georgia. I have several research questions I am investigating by examining how both client level characteristics and the characteristics of the housing programs that they participate in contribute to housing placement for clients discharged from homeless assistance programs in Georgia. Resources such as mental health, medical care, food pantries, and other services are more closely located inside of the City of Atlanta where there is public transit making them easier to access without a care than in areas outside of the city with more sprawling areas. These supportive services can help stabilize a client, which can be beneficial in obtaining housing. This brings me to my first question: are successful housing placements more likely to be achieved by clients in programs located in the City of Atlanta, as measured by the variable i*nside City of Atlanta*, than those clients in programs located outside of the city? Georgia has a higher rate of individuals who are homeless than other states (Henry et al., 2017). This could mean that fewer individuals in households without children are exiting homelessness. Does having children in a household lead to better housing outcomes? Previous research suggests that having prior experience with homelessness can increase risk for future episode of homelessness and that the longer someone has experienced homelessness, the more difficult it can be for him or her to exit (O'Connell, Kasprow, & Rosenheck, 2008; Caton et al., 2005). Does the relationship between length of stay in previous place and obtaining permanent housing at program exit depend on the prior residence? More specifically, does the longer a client has been homeless immediately prior to entering a housing project decrease the odds successful exit to permanent housing, regardless of program type? And lastly, recent research has shown that racial disparities exist in the homeless services system (Olivet et al., 2018). This could be because more black or African American clients are entering the homeless services system that white clients, or it could mean that black of African American clients are struggling to exit homelessness. For this sample in Georgia, are black or African American clients less likely to exit homelessness regardless of housing intervention type?

Methods

Sample

In Georgia, there are nine continua of care (CoCs), which are local planning bodies that are responsible for coordinating homelessness services in their geographic area. All of Georgia's CoCs participate in a coordinated system of data collection called the Homeless Management Information System (HMIS). Homeless service providers enter client level data into the system, and the CoCs are able to track and report outcomes and progress with that data. It should be noted that federally funded programs are required to enter client data into HMIS, although not all of the programs included in HMIS are federally funded. For this analysis, I used client level data collected in Georgia's HMIS system for this analysis. Data was exported from the Georgia HMIS system for clients who exited from a housing program between October 1st, 2016, and September 30th, 2017. All data was deidentified prior to analysis. The target population for this research was households experiencing homelessness in the state of Georgia who were enrolled in a housing assistance program. The data collected in the Georgia HMIS system were 'Universal Data Elements,' which are required to be entered into the system by the U.S. Department of Housing and Urban Development (HUD, 2017). These data are all self-reported. The data included in this modeling exercise were basic demographics such as sex, race, family type, disability status, and veteran status as well as housing program and housing outcome information.

Measures

Outcome

Housing placement is a dichotomous variable defined as whether the client exited to a permanent housing destination (1=Client exited to a permanent housing destination, 0=Client exited to any non-permanent housing destination). This is adapted from HUD's specifications for the variable "Destination" (U.S. Department of Housing and Urban Development, 2017). More detail can be found in Appendix A.

Individual-level variables

Several variables from Georgia HMIS were used as individual-level predictors. Predictors were chosen due to their availability in the dataset as well as previous research Dichotomous and categorical predictors are dummy coded, as described below. *Age* is a continuous variable created by subtracting client date of birth from program enrollment date, and is group-mean centered per the recommendations by Enders and Tofighi (2007) pertaining to level-1 predictors. Age is group-mean centered because there are some programs that serve specific populations, such as the youth (young adults between the ages of 18 and 24), which should be accounted for in the analysis. *Race* is dummy coded as two dummy variables, with 'Asian' and 'American Indian and Alaska Native' and 'Multiracial' collapsed into one category called 'Other or Multiracial' as well as 'White' as an additional category with 'black or African American' as the reference group. Coding specifications for race are located in Appendix A. The race dummy variables were uncentered because I did not have any questions pertaining to contextual effects of race on the outcome.

Gender is a dichotomous variable (1=Male, 0=Female) and is uncentered. *Family* is a variable that were created using the variable RelationshipToHoH to determine wither a households had children or not. From this, I created a dichotomous variable (1=Family, 0=Individual) which is uncentered. *Mental Illness* is a dichotomous variable (1=Mental Illness, 0=No Mental Illness) and is uncentered; *Substance Abuse* is another dichotomous variable (1=Substance, 0=No Substance Abuse) and is also uncentered. *Veteran* status is a dichotomous variable (1=Veteran, 0=Not veteran) and is uncentered. These variables are client demographics; the following variables are related to the clients' enrollment in a housing program. *Income Increase* this is a variable that measures client income (cash and non-cash income) change from program enrollment to discharge. This is a continuous variable calculated by subtracting, and is group-mean centered per the recommendations by Enders and Tofighi (2007) pertaining to level-1 predictors. Income increase is group-mean centered because some programs offer employment training and other supportive services that increase cash or noncash income, which should be taken into consideration. *Length of program enrollment* (LOPE) is a continuous variable calculated by subtracting EnrollDate from ExitDate to determine the number of days that a client was enrolled in a housing program, and is group-mean centered because some programs offer differing program enrollment lengths.

HUD homeless can be more clearly defined as homeless status at program entry. This determination is made according to HUD's definition of homelessness as defined in the HEARTH Act (Homeless Emergency Assistance and Rapid Transit to Housing Act, 2009). This is a dichotomous variable (1=Client was homeless according to HUD's homeless definition when s/he entered the program, 0=Client was not homeless according to HUD's homeless definition when s/he entered the program) and is uncentered. This variable is coded according to the HUD Data Dictionary, variable Living Situation (A), field name "Type of Residence" (U.S. Department of Housing and Urban Development, 2017). Housing situations considered to be homeless by HUD (1- Emergency shelter, including hotel or motel paid for with emergency shelter, 16 – Place not meant for human habitation, 18 – Safe haven, 27 - Interim Housing) were coded as 1 and all other responses were coded as 0.

Length of Stay in Previous Place (LOSPP) is an ordinal variable for the length of time that the client lived in his/her previous place of residence (less than one week, one week to 90 days, 91 days to one year, longer than one year). This variable is left uncentered. This variable was dummy coded as 3 variables with the reference group representing "Less than one week," *LOPSS1* representing "One week to 90 days," *LOSPP2* representing "91 days to one year," and *LOSPP3* representing "Longer than one year." This was adapted from the variable "Length of stay in prior living situation." More detail regarding the coding is provided in Appendix A. By taking the midpoint of each of these time categories, and creating a continuous version of the variable *LOSPP*, I assessed whether a continuous predictor would yield a better fit to the data; results indicated that the model with a continuous predictor in place of the ordinal predictors did not have superior fit, and thus the ordinal predictor was used in the analysis. The categorical predictors *race, gender, mental illness, substance abuse, veteran status, family,* and *LOSPP* are left uncentered because this is an exploratory analysis and none of the research questions demand that contextual effects be assessed.

Program-level variables

Inside City of Atlanta is specified by the location of the program and is a dichotomous variable (1=within Atlanta city limits, 0=outside of Atlanta city limits Atlanta, GA). This variable is uncentered. *Program Type* is indicative of the housing intervention type (Emergency shelter, transitional housing, permanent supportive housing, and rapid rehousing). This was dummy coded in 3 variables with rapid rehousing as the reference group. All dummy variables for *Program Type* are uncentered.

Analytic Strategy

Data cleaning was done in RStudio Version 1.0.136, and all analysis was done in SAS Software, Version 9.4 (SAS Institute, Cary NC) using PROC GLIMIX. For this analysis, I first examined all descriptive statistics before moving on to running an unconditional model. Once it was established that a hierarchical model was appropriate for this data, I built a base model (Model 1) which included basic demographic, enrollment, and programmatic characteristics. For each of the four following models, one variable was tested to assess each research question. This resulted in one final full model (Model 5) which included all variables of interest in the dataset.

Results

Table 1 shows the descriptive statistics for both level 1 and level 2 variables used in the analysis. There were 8,756 clients included at level 1. Most clients identified as Black or African American (71.96%), male (57.15%), and individuals in households without children (83.65%). Average client age was 42.05 years (SD = 14.20). A sizeable portion of clients indicated they had mental illness (31.41%) with fewer indicating they struggled with substance abuse (10.51%). Nineteen percent of clients were veterans and 61.6% were homeless the night before they entered their housing project. Most clients had stayed in their previous residence from one week to 90 days (39.28%). Client were enrolled for an average of 118.13 days (SD = 290.63). The average income increase experienced for client during project enrollment was $181.41 (SD = 1901.15). There were 311 projects included as level 2, the majority of which were located outside of the city of Atlanta (71.38%). Most projects in the sample were permanent supportive housing projects (31.51%). Table 2 shows the descriptive statistics for all client level factors by housing intervention type.

The interclass correlation value for the unconditional model was 0.3982, meaning that 40% of the variability in housing placement is accounted for by program factors. The unconditional model is as follows:

$$\text{Level 1: } \log[\phi_{ij} / (1 - \phi_{ij})] = \beta_{0j}$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + u_{0j}$$

where β_{0j} represents the log odds of a client, i, successfully obtaining permanent housing at program exit for housing program j. In level-2, γ_{00} represents the overall expected log odds for housing outcome across all programs, and $u_{0j} \sim \mathrm{N}(\mu_{ij}, \sigma^2)$ represents the difference between the overall log odds of successful housing outcome and the log odds of successful housing outcome for housing program *j*.

Hierarchical Generalized Linear Modeling is able to handle observations that are missing at random; data in this sample were assumed missing at random. Five conditional models were fit to this data in order to test the proposed research questions. Note that all models in this analysis are hierarchical logistic regression and assume a Bernoulli distribution for the outcome. The parameter estimates for all conditional models are shown in Table 3. Predictors presented in conditional Model 1 are included in all models in this analysis because they were found in previous research to have a relationship with homelessness. These variables can be grouped as demographic factors (*age, race, gender, family, mental illness, substance abuse, and veteran status)* and client enrollment factors (*income increase*, *LOPE*, *HUD homeless, and LOSPP*). The level 2 variable *program type* is included in all models as housing outcomes are dependent on the type of program from which a client is exiting. The conditional model for Model 1 is:

$$\text{Level 1: } \log[\phi_{ij} / (1 - \phi_{ij})] = \beta_i + \beta_1(AGE_{ij} - \overline{AGE}_{.j}) + \beta_2 WHITE_i + \beta_3 OTHER\ RACE_i + \beta_4 GENDER_i + \beta_5 MENTAL\ ILLNESS_i + \beta_6 SUBSTANCE\ ABUSE_i + \beta_7 VETERAN\ STATUS_i + \beta_8(INCOME\ INCREASE_{ij} - INCOME\ INCREASE_{.j}) + \beta_9(LOPE_{ij} - \overline{LOPE}_{.j}) + \beta_{10} HUD\ HOMELESS_i$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \gamma_{01} PROGRAM\ TYPE_j + u_{0j}$$

where $\log[\phi_{ij} / (1 - \phi_{ij})]$ represents the log odds of a client, *i*, successfully obtaining permanent housing for housing program *j*, β_{0j} represents the log odds for client permanent housing outcome for housing program *j*, and β_{1j} through β_{9j} represent the each predictor's expected impact on client housing outcome. For the level-2 conditional model γ_{00} represents the log odds of success across programs relative to the respective level-1 predictor, and γ_{01} represents the log odds of success for *program type* on the outcome.

For Model 2, level-1 is identical to that in Model 1.

Model 2:

$$\text{Level 1: } \log[\phi_{ij} / (1 - \phi_{ij})] = \beta_i + \beta_1(AGE_{ij} - \overline{AGE}_{.j}) + \ldots + \beta_{10}PRIOR\ NIGHTS\ RESIDENCE_i$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \gamma_{01}PROGRAM\ TYPE_j + \gamma_{02}INSIDE\ CITY\ OF\ ATLANTA_j + u_{0j}$$

The predictor *Inside City of Atlanta* is added to level-2, as represented by γ_{02} which represents the log odds of successful permanent housing placement for *Inside City of Atlanta*.

For Model 3:

$$\text{Level 1: } \log[\phi_{ij} / (1 - \phi_{ij})] = \beta_i + \beta_1(AGE_{ij} - \overline{AGE}_{.j})_i + \ldots + \beta_{11}FAMILY_i$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \gamma_{01}PROGRAM\ TYPE_j + u_{0j}$$

where the predictor *family* is added to level-1, as represented by β_{10} and level-2 is identical to that in Model 1 with *program type* as the only predictor.

For Model 4:

$$\text{Level 1: } \log[\phi_{ij} / (1 - \phi_{ij})] = \beta_i + \beta_1(AGE_{ij} - \overline{AGE}_{.j})_i + \ldots + \beta_{12}LOSPP_i + \beta_{13}LOSPP2_i + \beta_{14}LOSPP3_i$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \gamma_{01}PROGRAM\ TYPE_j + u_{0j}$$

where the predictors for the dummy coded variable *length of stay in prior residence (LOSPP)* is added to level-1, as represented by $\beta_{12}, \beta_{13}, \beta_{14}$ (*LOSPP1* = one week to 90 days, *LOSPP2* = 91 days to one year, and *LOSPP3* = longer than one year), and level-2 is identical to that in Model 1 with *program type* as the only predictor.

For Model 5:

$$\text{Level 1: } \log[\phi_{ij} / (1 - \phi_{ij})] = \beta_i + \beta_1(AGE_{ij} - \overline{AGE}_{.j}) + \beta_2 WHITE_i + \beta_3 OTHER\ RACE_i + \beta_4 GENDER_i + \beta_5 MENTAL\ ILLNESS_i + \beta_6 SUBSTANCE\ ABUSE_i + \beta_7 VETERAN\ STATUS_i + \beta_8(INCOME\ INCREASE_{ij} - INCOME\ INCREASE_{.j}) + \beta_9(LOPE_{ij} - \overline{LOPE}_{.j}) + \beta_{10} PRIOR\ HOMELESSNESS_i + \beta_{11} FAMILY_i + \beta_{12} LENGTH\ OF\ STAY\ IN\ PREVIOUS\ PLACE_i + \beta_{12} LOSPP1_i + \beta_{13} LOSPP2_i + \beta_{14} LOSPP3_i + \beta_{15} HUD\ HOMELESS{*}LOSPP1_i + \beta_{16}\ HUD\ HOMELESS{*}LOSPP2_i + \beta_{17}\ HUD\ HOMELESS{*}LOSPP3_i$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \gamma_{01} PROGRAM\ TYPE_j + \gamma_{02} INSIDE\ CITY\ OF\ ATLANTA_j + u_{0j}$$

where the interaction terms for *length of stay in prior place* and *HUD homeless* have been added and are represented by $\beta_{15}, \beta_{16}, \beta_{17}$. The results of these interaction terms are presented in Table 4.

The Table 3 includes the parameter estimates, odds ratios, and confidence intervals for the odds ratios. Odds ratios were calculated by exponentiating the parameter estimates. As consistent with previous research, in Model 5 *gender*, *family, mental illness, length of program enrolment (LOPE)*, *HUD homeless,* and length of stay of *366 days of more in previous place (LOSPP3)* were statistically significantly related to housing outcomes at level-1. Holding constant other factors in the model, the odds of successfully obtaining permanent housing at program exit for men were 0.79. For individuals with mental illness, the odds of permanent housing achievement at exit were 0.81, accounting for age, race, gender, family, mental illness, substance abuse, veteran status, income, length of program enrollment, length of stay in previous place, HUD homeless, program type, and inside City of Atlanta. For those who were homeless at program entry, the expected odds of permanent housing at exit were 0.82. The predictor *family* was added to assess its impact on the outcome. Households with children had 1.71 times the odds of obtaining permanent housing than households without children, accounting for all other variables in the model.

The level-2 predictor *program type* did have a statistically significant impact on housing outcomes. The odds of exiting from an emergency shelter, controlling for other factors in the model were 0.19 compared to rapid rehousing; odds of exiting from a transitional housing program or permanent supportive housing program, controlling for other factors in the model were 0.52 and 0.38, respectively, compared to rapid rehousing. Comparisons between each other project type are included in Table 5. *Inside City of Atlanta* was not a significant predictor from housing outcome at exit. For individuals who were receiving housing services from programs located inside the City of Atlanta and who were enrolled for an average number of days, were an average age, and had an average income, the expected odds of obtaining permanent housing at program exit were 1.06 times the odds for individuals who were receiving housing services outside of Atlanta, age, race, gender, family, mental illness, substance abuse, veteran status, income, length of program enrollment, length of stay in previous place, HUD homeless, and program type.

In model 4, the main effect for *length of stay in previous place* was statistically significant, and from Model 1, we established that *HUD homeless* also had a statistically significant relationship with successful housing outcome. For Model 5, the expected odds of permanent housing placement for an individual who was homeless at program entry and had been homeless for one year or longer were 0.52 times the odds for an individual who was not homeless at program entry and who had been in their previous residence for less than one year, controlling for age, race, gender, family, mental illness, substance abuse, veteran status, income, length of program enrollment, program type, and inside City of Atlanta. These results are presented in Table 4.

Discussion

Findings in this study are consistent with and supported by previous research. Demographic factors such as age, gender, and mental illness impacted housing outcomes in this sample from the state of Georgia. Individuals who are older, male, and have mental illness were less likely to obtain permanent housing, regardless of which type of program they were enrolled in. Race was not statistically significantly related to housing outcomes in the final model, but because it was related in several of the previous models. This, however, does not indicate that race has no relationship to homelessness. This data includes a fairly limited sample of the homeless population, and also does not include information on the long term housing stability of the individuals who have exited to permanent housing destinations, as returns to homelessness are not measured in this dataset. Recent literature shows that there are racial disparities in homelessness and poverty in several communities in the United States, one if which is the City of Atlanta (Olivet et al., 2018). To be clear, this study is not necessarily indicative of the prevalence of homelessness for racial groups and the results presented in the study do not indicate a lack of racial disparities in Georgia's homeless service system.

The programmatic factors increase in income during program enrollment and average LOPE did not make significant contributions to housing outcome. HUD homeless did impact permanent housing placement, although it should be noted that federally funded homeless assistance programs do exclusively service clients who were considered literally homeless (sleeping in a place not meant for human habitation, an emergency shelter, or a hotel or motel paid for by a homeless assistance agency) the night before they entered the program.

Results show that households with children are better able to secure permanent housing upon the conclusion of their housing assistance. This is a crucial finding because it shows that there may be a lack of effective services in place to assist individuals in adult only households or single adult households. The state of Georgia experienced the second highest decrease in homelessness in the nation among families with children, but there is a disproportionally high number of individuals who are experiencing homelessness in rural Georgia when compared to the rest of the nation (Henry et al., 2017). This is indicates that there is a need for more wrap around services targeting this subpopulation and more research to determine what barriers this population may be facing or having more difficulty overcoming than households with children.

I theorized that more successful housing placements would be obtained by clients enrolled in programs located in the City of Atlanta than those clients enrolled in programs located outside of the city. This was not supported by the data; however, in future research, it could be beneficial to have more than just a simple dichotomy of inside the City of Atlanta versus not. Just outside of the City of Atlanta and in other parts of Georgia, there are certainly other urban and suburban areas and the data available for this analysis is not sensitive to those geographic variations. It is particularly important that studies begin to examine rural homelessness as there is little published research on the subject.

Results indicate that the longer someone has been homeless, the less likely he or she is to obtain permanent housing at program exit was supported by Georgia HMIS data in this analysis. This is supported by current literature (O'Connell, Kasprow, & Rosenheck, 2008) and is also an indication that HUD's emphasis on prioritizing those who have experienced homelessness for a longer is for good cause. Those who are experiencing homelessness for one year or longer are more likely to remain homeless, thus the more swiftly a housing intervention can be offered, the more likely a stable, permanent housing solution can be attained.

A client's ability to obtain permanent housing at program exit, was impacted by the type of housing assistance program that he or she was enrolled in. More specifically for clients enrolled in Emergency Shelter, Transitional Housing, or Permanent Supportive Housing, the odds of exiting one of those programs to a permanent housing destination were all lower than for those clients enrolled in Rapid Rehousing, holding other factors constant. This was an important aspect of this study as few studies had directly examined the housing outcomes of various housing assistance program types simultaneously. It should be noted, however, that this research is in no way an evaluation of these housing intervention types. Also, as previously mentioned, there is no longitudinal data in this dataset to determine the long term stability for these clients, thus the efficacy of the programs was not fully measured However, as the populations of the programs that form the homeless service system in Georgia do vary, in the future when evaluating the efficacy and efficiency of a housing assistance program, it is imperative that both the characteristics of the clients within the program as well as the characteristics of the program itself be taken into account. The outcome variable, *housing placement* was dichotomized for this analysis as either permanent housing or non-permanent housing. In future research, it could be beneficial to look at predictors or various housing placement types, such as institutional, homeless, temporary, and permanent in order to further investigate the impact that client characteristics and program characteristics have on housing placement.

The limitations in this study largely stem from what is not captured in this data. There are additional variables that could be related to homelessness, such as education levels, eviction history, availability of affordable housing, and involvement in the criminal justice system, none of which are collected in the HMIS system. HMIS data regarding victims of domestic violence is not available for analysis in order to protect those individuals. However, in Georgia, a sizeable portion of those experiencing homelessness are victims of domestic violence. In addition, not all persons experiencing homelessness choose to receive services, and not all organizations that provide housing services for homeless individuals and families choose to participate in the HMIS system. Smaller, more remote shelters, churches, or other social service organizations and unsheltered, difficult to locate, or more service resistant men and women might not be represented in this data.   This data is limited to the organizations who participate in HMIS as well as the individuals and families who receive services from those organization. This sample included clients from programs that were federally funded and other programs that were not federally funded. In federally funded housing programs, clients must be literally homeless according to HUD's definition in order to be enrolled in the program. This means that there could be an inconsistency in the prevalence of HUD homeless clients across programs. Because of this, caution must be used when interpreting this variable. Additionally, the interaction between the categorical dummy variables for *LOSPP* and *HUD homeless* must be interpreted with some caution as well. There is debate over the interpretation of interaction terms in nonlinear models as the magnitude of an interaction effects is impacted by all of the covariates in the model (Ai & Norton, 2003).   The statistical significance of marginal effect of the interaction term is not calculated in standard statistical software, as used in this analysis.

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Table 1.
Demographics of Sample Population

Characteristic	*n* (%)
Total # of Individuals	**8,756**
Outcome	
Permanent housing placement	3377 (38.60)
Non-permanent housing placement	5372 (61.40)
Missing	7 (0.00)
Level-1 Characteristic	
Age (Years), *Mean* (*SD*)	42.05 (14.20)
Race	
Black or African American	6,301 (71.96)
White	2,217 (25.32)
Multiracial/Other	95 (1.08)
Missing	143 (1.63)
Gender	
Male	5,004 (57.15)
Female	3,751 (42.84)
Missing	1 (0.00)
Family	
Individual	7,286 (83.65)
Family with Children	1,470 (16.35)
Mental Illness	
Yes	2,750 (31.41)
No	5,783 (66.05)
Missing	223 (2.54)
Substance Abuse	
Yes	920 (10.51)
No	7,836 (89.49)
Veteran Status	
Veteran	1,667 (19.04)
Not Veteran	6,981 (79.73)
Missing	108 (1.23)
Income Increase (Dollars), *Mean (SD)*	181.41 (1901.15)
Length of Program Enrollment (LOPE) (Months), *Mean* (*SD*)	9.84 (19.53)
HUD homeless	
Homeless	5,397 (61.64)
Non Homeless	3,212 (36.68)
Missing	147 (1.68)

Length of Stay in Previous Place (LOSPP)	
Less than one week	3,132 (35.77)
One week to 90 days	3,439 (39.28)
91 days to one year	1,280 (14.62)
Longer than one year	739 (8.44)
Missing	166 (1.90)
Total # of Programs	**311**
Level-2 Characteristics	
Inside City of Atlanta	
Urban	89 (28.62)
Not Urban	222 (71.38)
Program Type	
Emergency Shelter	87 (27.97)
Transitional Housing	57 (18.33)
Permanent Supportive Housing	98 (31.51)
Rapid Rehousing	69 (22.19)

Table 2.

Client Level Demographics by Program Type

Characteristic	Emergency Shelter *n* (%)	Transitional Housing *n* (%)	Permanent Supportive Housing *n* (%)	Rapid Rehousing *n* (%)
Total # of Individuals	**5,799**	**775**	**675**	**1,507**
Outcome				
Permanent housing placement	1,571 (27.09)	401 (51.74)	358 (53.04)	460 (30.52)
Non-permanent housing placement	4,225 (72.86)	372 (48.00)	315 (46.67)	1,047 (69.48)
Missing	3 (0.05)	2 (0.26)	2 (0.30)	0 (0.00)
Level-1 Characteristic				
Age (Years), *Mean* (*SD*)	41.36 (7.87)	44.11 (7.53)	43.43 (8.24)	42.99 (6.61)
Race				
Black or African American	4,102 (70.74)	570 (73.55)	429 (63.56)	1,200 (79.63)
White	1,518 (26.18)	187 (24.13)	240 (35.56)	272 (18.05)
Multiracial/Other	67 (1.16)	10 (1.29)	4 (0.59)	14 (0.93)
Missing	112 (1.93)	8 (1.03)	2 (0.30)	21 (1.39)
Gender				
Male	3,332 (57.46)	586 (75.61)	336 (49.78)	750 (49.77)
Female	2,466 (42.52)	189 (24.39)	339 (50.22)	757 (50.23)
Missing	1 (0.02)	0 (0.00)	0 (0.00)	0 (0.00)
Family				
Individual	5,169 (89.14)	664 (85.68)	600 (88.89)	853 (56.60)
Family with Children	630 (10.86)	111 (14.32)	75 (11.11)	654 (43.40)
Mental Illness				
Yes	1,499 (25.85)	271 (34.97)	547 (81.04)	433 (28.73)
No	4,206 (72.53)	493 (63.61)	124 (18.37)	960 (63.70)
Missing	94 (1.62)	11 (1.42)	4 (0.59)	114 (7.56)
Substance Abuse				
Yes	402 (6.93)	223 (28.77)	192 (28.44)	103 (6.83)
No	5,397 (93.07)	552 (71.23)	483 (71.56)	1404 (93.17)
Veteran Status				
Veteran	644 (11.11)	183 (23.61)	79 (11.70)	761 (50.50)
Not Veteran	5,055 (87.17)	588 (75.87)	594 (88.00)	744 (49.37)
Missing	100 (1.72)	4 (0.52)	2 (0.30)	2 (0.13)
Income Increase (Dollars), *Mean (SD)*	89.91 (217.39)	293.26 (608.47)	305.40 (564.87)	420.44 (591.37)
Length of Program Enrollment (LOPE) (Months), *Mean* (*SD*)	2.68 (7.85)	13.18 (7.56)	61.13 (33.90)	12.7 (6.75)
HUD homeless				
Homeless	3,522 (60.73)	325 (41.94)	412 (61.04)	1,138 (75.51)
Non Homeless	2,163 (37.30)	440 (56.77)	253 (37.48)	356 (23.62)
Missing	114 (1.97)	10 (1.29)	10 (1.48)	13 (0.86)
Length of Stay in Previous Place (LOSPP)				
Less than one week	2,690 (46.39)	196 (25.29)	77 (11.41)	169 (11.21)
One week to 90 days	1,933 (33.33)	353 (45.55)	318 (47.11)	835 (55.41)
91 days to one year	614 (10.59)	147 (18.97)	151 (22.37)	368 (24.42)
Longer than one year	424 (7.31)	70 (9.03)	125 (18.52)	120 (7.69)
Missing	138 (2.38)	9 (1.16)	4 (0.59)	15 (1.00)

Table 3.
Parameter Estimates, Standard Error Estimates, and Odds Ratio Estimates

Effect	Level 1 Main Effects			Level 1 and 2 Main Effects			Model 5 (Full Model)		
Level 1	Estimate	(*SE*)	Odds Ratio (95% CI)	Estimate	(*SE*)	Odds Ratio (95% CI)	Estimate	(*SE*)	Odds Ratio (95% CI)
Age	0.00	0.01	1.00 (0.98, 1.02)	0.00	0.01	0.98 (0.97, 1.00)	-0.02	0.01	0.98 (0.97, 1.00)
Race									
White	*-0.12	0.07	0.89 (0.78, 1.02)	*-0.12	0.07	0.89 (0.77, 1.02)	-0.12	0.07	0.89 (0.78, 1.02)
Other Racial Group	-0.10	0.27	0.91 (0.53, 1.54)	-0.11	0.27	0.89 (0.53, 1.51)	-0.13	0.27	0.88 (0.52, 1.49)
Male	*-0.28	0.07	0.75 (0.65, 0.88)	*-0.23	0.08	0.79 (0.68, 0.92)	*-0.23	0.08	0.79 (0.68, 0.92)
Family	*0.51	0.10	1.67 (1.39, 2.01)	*0.53	0.09	1.70 (1.42, 2.05)	*0.54	0.09	1.71 (1.42, 2.06)
Mental Illness	*-0.24	0.07	0.79 (0.69, 0.89)	*-0.22	0.07	0.80 (0.71, 0.91)	*-0.21	0.07	0.81 (0.71, 0.92)
Substance Abuse	-0.17	0.09	0.84 (0.70, 1.01)	-0.14	0.09	0.87 (0.72, 1.04)	-0.14	0.09	0.87 (0.72, 1.04)
Veteran	0.13	0.11	1.14 (0.93, 1.40)	0.10	0.11	0.90 (0.73, 1.11)	-0.10	0.11	0.90 (0.73, 1.11)
Income Increase	0.00	0.00	1.00 (1.00, 1.00)	0.00	0.00	1.00 (1.00, 1.00)	0.00	0.00	1.00 (1.00, 1.00)
Length of Program Enrollment	*0.01	0.00	1.01 (1.01, 1.02)	*0.01	0.00	1.01 (1.00, 1.02)	*0.01	0.00	1.01 (1.00, 1.02)
HUD Homeless	*-0.13	0.06	0.88 (0.78, 0.99)	*-0.14	0.06	0.87 (0.77, 0.98)	*-0.20	0.10	0.82 (0.67, 0.99)
LOSPP									
7 to 90 Days in Previous Place	0.18	0.07	1.19 (1.05, 1.36)	0.08	0.07	1.08 (0.95, 1.23)	-0.07	0.10	0.93 (0.76, 1.15)
91 to 365 Days in Previous Place	0.09	0.09	1.10 (0.92, 1.31)	0.11	0.09	1.12 (0.94, 1.33)	0.10	0.13	1.11 (0.85, 1.44)
366 Days or more in Previous Place	0.23	0.11	0.85 (1.01, 1.57)	0.12	0.11	1.13 (0.91, 1.41)	*0.33	0.16	1.39 (1.03, 1.89)
HUD Homeless*7 to 90 Days in Previous Place	---	---	---	---	---	---	0.19	0.13	
HUD Homeless*91 to 365 Days in Previous Place	---	---	---	---	---	---	-0.03	0.17	
HUD Homeless*366 Days or more in Previous Place	---	---	---	---	---	---	*-0.45	0.22	
Level 2									
Emergency Shelter	---	---	---	*-1.64	0.21	0.19 (0.13, 0.29)	*-1.64	0.21	0.19 (0.13, 0.29)
Transitional Housing	---	---	---	*-0.65	0.24	0.52 (0.32, 0.84)	*-0.66	0.24	0.52 (0.32, 0.83)
Permanent Supportive Housing	---	---	---	*-0.97	0.28	0.38 (0.22, 0.66)	*-0.97	0.28	0.38 (0.22, 0.66)
Inside City of Atlanta	---	---	---	0.12	0.16	1.12 (0.82, 1.53)	0.12	0.16	1.13 (0.82, 1.54)

Note. SE = Standard Error; CI = Confidence Interval; **p* < .05

Table 4.

Parameter Estimates and Odds Ratio Estimates for Model 5 interaction terms

Interaction	Estimate	OR
HUD homeless* less than 7 days in previous place	-0.20	0.82
HUD homeless*7 to 90 Days in Previous Place	-0.39	0.68
HUD homeless* 91 to 365 Days in Previous Place	-0.23	0.79
HUD homeless* 366 Days or more in Previous Place	-0.65	0.52

Table 5.

Parameter Estimates and Odds Ratio Estimates for Housing Intervention Types

Comparison	Estimate	OR
ES vs TH	-2.30	0.10
TH vs PSH	0.31	1.36
ES vs PSH	-0.67	0.51

Appendix A: Crosswalk for HUD Variable Conversions into Variables for Analysis

HUD Data Element and Coding	**HUD Description**	**Variable Created - Variable Coding for New Categories**	**Description of New Categories**
Destination	-	Permanent Housing Placement	
1	Emergency shelter, including hotel or motel paid for with emergency shelter voucher	31, 26, 28, 20, 19, 25, 11, 22, 21, 23, 3, 10	Permanent housing placement
2	Transitional housing for homeless persons (including homeless youth)	24, 7, 18, 17, 27, 12, 1, 15, 16, 13, 4, 5, 6, 14, 19	Non-permanent housing placement
3	Permanent housing (other than RRH) for formerly homeless persons	8, 9, 99, 30	Missing
4	Psychiatric hospital or other psychiatric facility		
5	Substance abuse treatment facility or detox center		
6	Hospital or other residential non-psychiatric medical facility		
7	Jail, prison or juvenile detention facility		
8	Client doesn't know		
9	Client refused		
10	Rental by client, no ongoing housing subsidy		
11	Owned by client, no ongoing housing subsidy		
12	Staying or living with family, temporary tenure (e.g. room, apartment or house)		
13	Staying or living with friends, temporary tenure (e.g. room apartment or house)		
14	Hotel or motel paid for without emergency shelter voucher		
15	Foster care home or foster care group home		
16	Place not meant for habitation (e.g., a vehicle, an abandoned building, bus/train/subway station/airport or anywhere outside)		
17	Other		
18	Safe Haven		
19	Rental by client, with VASH housing subsidy		
20	Rental by client, with other ongoing housing subsidy		
21	Owned by client, with ongoing housing subsidy		
22	Staying or living with family, permanent tenure		
23	Staying or living with friends, permanent tenure		
24	Deceased		
25	Long-term care facility or nursing home		
26	Moved from one HOPWA funded project to HOPWA PH		
27	Moved from one HOPWA funded project to HOPWA TH		
28	Rental by client, with GPD TIP housing subsidy		
29	Residential project or halfway house with no homeless criteria		
30	No exit interview completed		
31	Rental by client, with RRH or equivalent subsidy		
99	Data not collected		

Race		Race	
1	American Indian or Alaska Native	3	Black or African American
2	Asian	5	White
3	Black or African American	1, 2, 4	Multiracial/Other
4	Native Hawaiian or Other Pacific Islander	8, 9, 99	Missing

5	White		
8	Client Doesn't Know		
9	Client Refused		
99	Data Not Collected		

Gender		Gender	
0	Female	1, 3	Male
1	Male	0, 2	Female
2	Trans Female (MTF or Male to Female)	4, 8, 9, 99	Missing
3	Trans Male (FTM or Female to Male)		
4	Gender Non-Conforming (i.e. not exclusively male or female)		
8	Client Doesn't Know		
9	Client Refused		
99	Data Not Collected		

Type of Residence		HUD Homeless	
Homeless		16, 1, 18, 27	Literally homeless at entry
16	Place not meant for habitation	15, 6, 7, 24, 4, 5, 14, 23, 21, 3, 2, 19, 25, 20, 26, 12, 13, 2	Not literally homeless at entry
1	Emergency shelter, including hotel or motel paid for with emergency shelter voucher	8, 9, 99	Missing
18	Safe Haven		
27	Interim Housing		
Institutional			
15	Foster care home or foster care group home		
6	Hospital or other residential non-psychiatric medical facility		
7	Jail, prison or juvenile detention facility		
24	Long-term care facility or nursing home		
4	Psychiatric hospital or other psychiatric facility		
5	5 Substance abuse treatment facility or detox center		
Transitional And Permanent			
14	Hotel or motel paid for without emergency shelter voucher		
23	Owned by client, no ongoing housing subsidy		
21	Owned by client, with ongoing housing subsidy		
3	Permanent housing (other than RRH) for formerly homeless persons		
22	Rental by client, no ongoing housing subsidy		
19	Rental by client, with VASH subsidy		
25	Rental by client, with GPD TIP subsidy		
20	Rental by client, with other housing subsidy (including RRH)		
26	Residential project or halfway house with no homeless criteria		
12	Staying or living in a family member’s room, apartment or house		
13	Staying or living in a friend’s room, apartment or house		
2	Transitional housing for homeless persons (including homeless youth)		
Missing			
8	Client doesn’t know		
9	Client refused		

99	Data not collected		

Length of stay in prior living situation		LOSPP	
10	One night or less	10, 11	Less than one week
11	Two to six nights	2	One week to 90 days
2	One week or more, but less than one month	3, 4	91 days to one year
3	One month or more, but less than 90 days	5	Longer than one year
4	90 days or more, but less than one year	8	Missing
5	One year or longer		
8	Client doesn’t know		