Housing the Homeless:

The Effect of Housing Assistance on Recidivism to Homelessness, Economic, and Social Outcomes

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Job Market Paper

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Abstract: Funding for housing assistance programs serving the homeless has more than doubled in the past decade, with only scant evidence regarding the causal effect of housing assistance on recidivism to homelessness and economic and social outcomes such as crime, employment, and health. Using a random case worker assignment design and a novel dataset constructed by linking administrative records from multiple public agencies in Los Angeles County, I estimate that housing assistance for single adults experiencing homelessness reduces future recidivism to homelessness by 20 percentage points over an 18-month period, compared to a baseline mean of 40 percent. The decline is driven by housing programs that provide long-term housing solutions and by individuals with physical disabilities and/or severe mental illness. Moreover, my findings suggest that housing assistance reduces crime, increases employment, and improves health, while not increasing reliance on social benefits. A simple cost-benefit analysis implies that up to 80 percent of housing costs are offset by these potential benefits in the first 18 months alone. Taken together, these findings demonstrate that well-targeted housing assistance for the homeless with a focus on long-term housing solutions can be rehabilitative for a large segment of the homeless population.

Keywords: homelessness, housing assistance, recidivism
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1 Introduction

Homelessness is an extreme outcome of poverty that is growing rapidly in US cities. There are approximately 550,000 individuals who are homeless on a given night, and more than 1.4 million Americans who use some homeless services at least once a year.[1] Homelessness is associated with multiple adverse outcomes (e.g., increased mortality and morbidity, increased involvement in criminal activity, and reduced probability of finding housing and employment) which impose a heavy administrative and financial burden on public agencies and local governments, with some estimates showing that the average cost of direct public services alone is $83,000 per homeless person per year (Flaming et al., 2015).[2]

Housing assistance is the most common public policy for homelessness, yet there is only scant evidence about its effectiveness in preventing recidivism to homelessness and improving welfare due to lack of comprehensive longitudinal data on individuals experiencing homelessness, non-random selection of participants into housing assistance programs, and challenges in conducting randomized controlled trials (Evans et al., 2019; National Academies of Sciences et al., 2018; O'Flaherty, 2019). Moreover, while little is known about recidivism to homelessness and housing assistance receipt, recent studies show that a significant share of housing assistance recipients return to homelessness while or after receiving housing assistance (Cusack and Montgomery, 2017; Levitt et al., 2013). Nevertheless, funding for housing assistance programs serving individuals experiencing homelessness more than doubled in the past decade, reaching more than $18 billion nationally in 2019 (USICH, 2020; Johnson and Levin, 2018).

This paper studies the effect of housing assistance on recidivism to homelessness and other economic and social outcomes such as crime, employment, and health. I construct a novel and comprehensive panel dataset which allows me to compare outcomes of individuals experiencing homelessness who receive housing assistance to those who do not. I do that by linking administrative records across multiple public service agencies in Los Angeles County, which has the nation's second largest homeless population, including the homeless response system, health services, and the sheriff's department, among others. I then use these links to create a panel dataset at the case-month level containing public service histories of all single individuals experiencing homelessness in Los Angeles County who sought assistance between 2016 and 2017. This comprises data on homeless services received, including housing assistance, and a series of economic and social outcomes, including involvement in criminal activity, employment, and health care utilization.

I address potential non-random assignments into housing assistance programs using a

[1] Annual Homeless Assessment Reports to Congress, 2017-2019.

[2] See Culhane et al. (2002) and Khadduri et al. (2010) for more information on the costs of homelessness.

random case-worker assignment design ("Judge Fixed Effects") to construct an instrumental variable for housing assistance receipt. A naive comparison of individuals who receive housing assistance versus those who do not could lead to biased conclusions that result from selection into housing assistance treatment based on observed and unobserved characteristics of clients' and service providers' heterogeneity. I overcome this potential selection problem by exploiting a quasi-experiment where individuals are randomly assigned different probabilities of housing assistance receipt based on their case worker assignment. This quasi-experiment is the result of as-good-as-random assignment of clients' cases to case workers combined with considerable variation between case workers in their propensity to place individuals in housing programs, even after conditioning on service site, time, and case characteristics.

My paper provides four main results. First, I find that housing assistance discourages recidivism to homelessness, which I measure as future returns to the homeless support system. Using my instrument of case worker housing placement propensity, I estimate that housing assistance lowers the probability of returning to the homeless support system within 18 months by 20 percentage points compared to a baseline mean of 40 percent. Importantly, these results are not driven only by the ability of clients to remain housed while actively receiving assistance. I find considerable decreases in recidivism probabilities even after housing assistance has ended for a large portion of clients.

Second, the reduction in recidivism to homelessness is larger for individuals who are more likely to receive housing assistance based on their observed characteristics. That is, the estimated reduction in recidivism to homelessness among individuals who are more likely to receive housing assistance because of the acuity of their situation (because they have been homeless for a long time or they suffer from substantial disabilities, for instance) is estimated to be two to four times larger compared to the estimated reduction in recidivism to homelessness among low-acuity individuals. These heterogeneous effects suggest that (i) providing direct housing assistance to the most vulnerable individuals is highly beneficial, while alternative types of assistance (for example, direct cash assistance) can be more beneficial for low-acuity individuals and (ii) there is room for better targeting of housing program types and services among low-acuity individuals.

Third, I find that the effect of housing assistance on recidivism to homelessness is larger in programs that provide long-term housing solutions and when clients receive assistance for a longer duration. In particular, I find that the estimated reduction in recidivism to homelessness is driven by individuals in permanent housing programs (who also have longer duration), while the estimated impact among individuals in temporary housing programs (e.g., emergency shelters) is not different from receiving no housing assistance at all. Consistent with these findings, my analysis suggests that the reduction in recidivism to homelessness is driven almost exclusively by intensive margin responses, that is, by individuals receiving housing assistance for a longer duration (i.e., enrolling in a 6-month housing assistance program versus spending a week in an emergency shelter), while the extensive margin response (i.e., receiving an emergency shelter placement for a couple of nights versus none at all) is small and insignificant.

Fourth, I explore the impact of housing assistance on additional economic and social outcomes. My findings suggest that housing assistance improves health, reduces crime, and increases employment. Specifically, I estimate that housing assistance lowers the number of emergency department visits within 18 months by 80 percent compared to baseline mean, reduces the number of jail days within 18 months by 130 percent and the probability of committing a crime by 80 percent compared to baseline mean, and increases the probability of reporting employment by 24 percentage points within 18 months. Moreover, I find no significant relationship between housing assistance and receipt of various types of social benefits, ruling out potential increases in public spending that result from housing assistance.

My findings have important implications for policy debates over eligibility, duration and targeting of housing assistance types to individuals experiencing homelessness. One important policy question is whether the positive effects from housing are cost-effective. Back-of-the-envelope calculations presented at the end of the paper suggest that up to 80 percent of housing costs are offset by direct savings to public agencies within the first 18 months alone, which I compute as savings from reduced use of homeless and other public services and from increased employment. The overall benefits from housing assistance are likely to be larger due to indirect benefits from potential reduction in street homelessness and its associated burden on public agencies, health and law enforcement in particular, and the fact that the benefits are expected to grow over time as individuals spend more time off the streets. Consistent with that, I find although the cost of permanent housing programs is on average more than double that of temporary housing programs, the majority of cost savings arises from them, supporting a policy which increases eligibility and resources of housing assistance programs aimed at finding long-term housing solutions.

This paper advances the literature on homelessness in two dimensions. First, my study is the first to apply the random assignment of screener design ("Judge Fixed Effects") to study the causal effect of housing assistance for individuals experiencing homelessness.[3] Recent literature reviews by Evans et al. (2019), O'Flaherty (2019), and Kertesz and Johnson

[3]The number of studies that use the random screener design to identify a causal relationship has grown rapidly in recent years, and has been used in the context of incarceration (Aizer and Doyle, 2015; Bhuller et al., 2020; Kling, 2006), disability insurance (Autor et al., 2019; Dahl et al., 2014; Maestas et al., 2013), foster case (Bald et al., 2019; Doyle, 2007; Doyle, 2008); bankruptcy protection (Dobbie and Song, 2015); and foreclosures (Diamond et al., 2020).

(2017) show that while there is an extensive literature on homelessness, few papers have been able to come up with credible causal estimates of the effect of housing assistance on subsequent homelessness and additional outcomes of interest. This fact is driven in particular because of the numerous limitations of conducting randomized control trials (e.g., high costs, treatment assignment spillovers, attrition) and having access to high quality data on a large population of individuals experiencing homelessness. Second, I focus on single adults experiencing homelessness, an understudied yet important population, that represents more than two thirds of the homeless population. Much of the existing literature focuses on families who experience homelessness or on specific subgroups within the homeless population. For example, Evans et al. (2019) study the effect of housing vouchers for homeless veterans; Aubry et al. (2016) study the effect of Housing First programs in Canada on homeless individuals with serious mental illness; and Gubits et al. (2016) evaluate the effects of the Family Options study on family outcomes. The existing literature has tended not to provide general estimates for the single adult population as a whole group, despite the fact that they represent a big proportion of the homeless population.

This paper also relates to the growing literature on the effect of housing assistance on family and individual outcomes by focusing on a population group that has not received attention in the past due to data limitations. This literature has mainly focused on specific populations such as people who apply for housing vouchers, like in the Moving to Opportunity studies (Chetty et al., 2016), or who are forced to move after public housing demolitions, like Jacob (2004) and Chyn (2018). However, there are no studies in this literature that examine the impact of housing assistance for individuals experiencing homelessness, who are presumably those who need it the most, and potentially have the largest benefits from receiving housing assistance. Other studies, like van Dijk (2019), study broader populations of low-income families. However, these studies cannot usually identify homeless participants due to the lack of available data on participants. Finally, a few studies have examined the effect of housing evictions on homelessness, finding that they cause a large and persistent increase in risk of homelessness (Collinson and Reed, 2019; Fetzer et al., 2019).

The remainder of the paper proceeds as follows. Section 2 provides background on homelessness in Los Angeles County and briefly describes the different housing program types available to the homeless. Section 3 describes my data. Section 4 describes my research design and verifies its validity. Section 5 presents the main results on recidivism to homelessness. Section 6 presents further results on additional economic and social outcomes. Section 7 presents a cost-benefit analysis, and Section 8 concludes.

2 Background

Three features of the homeless response system in Los Angeles county make it an ideal setting to study homelessness. Los Angeles County has a large and growing homeless population, low availability of housing assistance for the homeless, and a universal record-keeping system that records all initial intakes and housing assistance provided by homeless service agencies. Housing assistance for the homeless in this setting is a diverse treatment that varies in duration, non-housing services provided, and ability to provide a permanent housing solution.

2.1 Homelessness in Los Angeles County

Los Angeles County has a large and growing number of individuals experiencing homelessness. Figure A.1 graphs the Los Angeles Continuum of Care's (CoC) homeless rate over time.[4] As of 2019, Los Angeles County has the nation's second largest homeless population, with approximately 60,000 individuals experiencing homelessness on a given night, with 45,000 of them living in places not meant for human habitation (The U.S. Department of Housing and Urban Development, 2019). The county's homeless rates reached these unprecedented levels after experiencing rapid growth over the past decade. Specifically, the county's homeless rate increased from 360 to 608 homeless individuals per 100,000 residents between 2010 and 2019, a 70 percent increase.

The demand for housing assistance to serve individuals experiencing homelessness is far greater than the supply of available housing in Los Angeles County. As of 2019, there was a total of 45,116 beds in 764 housing assistance programs that served the homeless or previously homeless population.[5] This number is roughly half of what is needed to address the county's needs (LAHSA, 2017). In addition, individuals currently being served are expected to occupy their units for a long period of time, implying considerably low vacancy rates. Specifically, the vacancy rate for these beds and units was 8 percent in 2019 (The U.S. Department of Housing and Urban Development, 2019).

2.2 Housing Assistance for the Homeless in Los Angeles County

Housing assistance for the homeless in Los Angeles County varies along three major dimensions: duration, availability and type of non-housing services, and the ability to provide a permanent

[4] Continuum of Cares (CoCs) are geographic units at which providers of homelessness assistance jointly apply for federal resources and develop a strategic plan to address homelessness within their jurisdiction. CoCs vary in size and composition and can be comprised of single cities, individual counties, several counties, or entire states. In 2019, there were 394 CoCs in the United States and its territories. Los Angeles CoC includes all of Los Angeles County except the cities of Glendale, Long Beach, and Pasadena. I will use the terms Los Angeles County and CoC interchangeably.

[5] Annual Homeless Assessment Report to Congress, 2019.

housing solution.[6] Based on these dimensions, housing programs that serve the homeless population in Los Angeles County can be broadly categorized into two types: temporary and permanent. Temporary housing programs, commonly known as emergency shelters, provide short-term housing assistance, and are meant to provide crisis housing for clients while they seek permanent housing solutions. Permanent housing programs provide medium- or long-term housing assistance with the intention of locating a permanent housing solution that can be used by clients after program participation and housing subsidy are completed.

Housing assistance programs also differ in the availability and amount of non-housing services they provide to their clients. Some of the most common non-housing services include case management, basic hygiene services (e.g., meals and showers, basic health care), substance abuse treatments, mental health treatments, life skills courses, and employment readiness workshops, among others. Permanent housing programs tend to provide more health care services, while temporary housing programs mostly offer basic hygiene services. However, there is a large degree of customization and hence variation in the amount or types of non-housing services provided, even among housing programs within the same category. These differences between programs are based both on clients' needs and providers' treatment philosophy. Moreover, many service providers in the county also offer separate non-housing assistance programs that are meant to complement housing assistance programs.

The third important difference between housing assistance programs is their ability to provide long-term housing solutions for clients. Permanent housing programs are based on the Housing First strategy for addressing homelessness. This strategy is based on quickly finding long-term housing solutions in order to minimize the trauma caused by homelessness and to better serve additional problems an individual experiencing homelessness is facing (Burt et al., 2017). These programs locate housing units for clients which they are supposed to occupy even after the housing subsidy period has ended. On the contrary, temporary housing programs are based on a continuum model for homelessness that emphasizes addressing clients' problems and getting them ready for housing prior to finding permanent housing.

2.3 Los Angeles County's Homeless Coordinated Entry System

The Los Angeles Continuum of Care (CoC), headed by the Los Angeles Homeless Services Authority (LAHSA), is the regional planning body that coordinates housing and services for homeless families and individuals in Los Angeles County. It includes hundreds of service providers who provide a variety of services, ranging from meals and hygiene services, health care, transportation, legal assistance, general case management, and temporary or permanent housing services, among others. Historically, the homeless response system of Los Angeles

[6] A more detailed description of these programs is available in Appendix A.2.

County was highly decentralized, with its service providers operating independently from one another and having little or no communication with one another.

In 2014, Los Angeles County's homeless service providers adopted and set up the Coordinated Entry System (CES) in response to the county's growing homeless crisis. The CES is a countywide system that brings together all service providers in order to quickly connect individuals to the most appropriate treatment for them. This system was designed to facilitate coordination and resource management for the multiple service providers that comprise the county's crisis response system by combining their information into one system.

The most important feature of the CES for the purposes of this study is the standardization and recording of all clients' intakes across all service providers. Beginning in 2016, as part of the adoption of the CES, all homeless individuals seeking assistance go through the same process when applying for assistance. Single adults experiencing homelessness who are seeking assistance can connect with the county's homeless service providers in one of three ways. First, clients can arrive independently to service providers through a "walk-in" option. Second, clients can be referred to service providers via other public agencies (e.g., health clinics, hospitals, social welfare programs). Third, many service providers operate street outreach teams that scan the streets of the county in order to assist unsheltered homeless individuals.

After clients have engaged with service providers, they are assigned to case workers who assess their acuity level and needs using a standardized assessment tool known as the VI-SPDAT (Vulnerability Index - Service Prioritization Decision Assistance Tool).[7] Their information is entered into the CES to determine their acuity and needs and to provide them with the appropriate care as quickly as possible.[8] After the assessment stage is completed, case workers work with their clients to build an action plan. As part of this plan, clients can receive a variety of different housing and non-housing services from various service providers across the county, according to their needs and availability.

Two features of the Los Angeles County homeless system are important for my analysis. First, when a client engages with a service provider in the system, they are assessed by the first available case worker, so conditional on service provider and time, the assignment

[7]The standardized VI-SPDAT assessment for single adults experiencing homelessness in Los Angeles County can be accessed through: `https://www.lahsa.org/documents?id=1306-form-1306-ces-survey-for-individuals-survey-packet.pdf`.

[8]In practice, the CES is still being developed and is not yet fully operational. To date, it serves as a system which prioritizes clients only for Permanent Supportive Housing (PSH) programs. LAHSA plans to expand the system in the future to encompass other services as well. It is important to emphasize that the standardized assessment tool serves as one of several tools the case worker has when deciding what types of services (if any) to provide the client, and does not determine whether the client is eligible for housing assistance. In my context, what matters is that all homeless single adults seeking assistance are required to enter the CES, which allows me to capture the universe of this population in Los Angeles County.

to a case worker is as-good-as-random.[9] Second, case workers differ in their propensity to place individuals in housing assistance programs. In my baseline specification, I measure the propensity of a case worker to place a client in a housing assistance program based on the share of cases that ended up receiving housing assistance among the other cases they have handled. When using this measure, I always condition on fully interacted service site by month of assessment fixed effects to account for the fact that randomization occurs within the pool of available case workers. This controls for any differences over time and/or across service providers in the availability of resources and the placement rates of case workers.[10]

3 Data and Descriptive Statistics

I create a case-level panel dataset containing information on homeless services received, housing assistance, and additional economic and social outcomes for the universe of cases for single individuals experiencing homelessness in Los Angeles County. I then limit my data such that only cases that were as-good-as-randomly assigned to a case worker are considered. I verify that these cases are representative of the overall sample of cases. I then present the distribution of housing assistance treatments in my sample and show that housing assistance is positively correlated with recidivism to homelessness, bearing out the potential selection into housing assistance treatments concerns that motivated my quasi-experimental research design.

3.1 Data Sources

I link data recording intakes of single individuals experiencing homelessness with homeless service providers to data sets containing administrative records from multiple public agencies in Los Angeles County.[11] I then use these linked records to construct a panel dataset containing information on homeless services received, housing assistance, and additional economic and social outcomes, such as crime, employment, and health.[12]

My main dataset consists of administrative records for individual intakes conducted by

[9] The random assignment of clients to case workers has been confirmed in multiple interviews I conducted with service providers and with representatives from the Los Angeles Homeless Services Authority (LAHSA). They have emphasized that this assignment is based on availability of case workers alone. This is true for all types of initial engagement of clients with providers (walk-ins, referrals, and outreach). I provide empirical evidence that assignments are as-good-as-random in Section 4.3.

[10] In Section 5.4, I show robustness of the results to alternative measures of the case worker housing placement rate.

[11] Table B.1 provides a summary of the various data sources used in this study, the information contained in them, and the time period they cover.

[12] Appendix B provides detailed information on how the various data sources were cleaned and prepared for analysis.

homeless service providers throughout Los Angeles County from 2016 to 2018. This data set, commonly known as the VI-SPDAT (Vulnerability Index - Service Prioritization Decision Assistance Tool), is a pre-screening tool that guides case workers when assessing the acuity level and needs of a particular individual. Each record includes a unique individual identifier, intake date, assessment details, and demographic characteristics (e.g., age, race, gender, disabilities, and veteran status). Additionally, each record provides information on the case worker conducting the intake process, including their name, organizational affiliation, and the location where the intake was conducted.

The second data source I use, called the Homeless Management Information System (HMIS), includes information on all homeless services provided (both housing and non-housing services) by homeless service providers in the Los Angeles CoC from January 2010 to June 2019. Additionally, it includes information on the type of service and/or housing program, and the enrollment and exit date (if relevant). For a sub-sample of the records in the HMIS, I observe information on reported income, employment, and social benefits.

The third data source I use, called the Enterprise Linkages Project (ELP), includes information across a spectrum of publicly funded health, mental health, social and corrections services in Los Angeles County, as well as the costs associated with those services and utilization. The ELP started in 2007 with the goal of providing comprehensive information on the multi-system service utilization patterns of persons participating in social welfare programs. It integrates records from the Departments of Health Services (DHS), Mental Health (DMH), Public Health (DPH), Public and Social Services (DPSS), as well as the Probation and Sheriff Departments.

I link the intake data to the HMIS and ELP data using the unique individual identifiers recorded in them to construct homeless and public service histories of all homeless cases. I use the HMIS data to define my main measure of housing assistance treatment, which is an indicator for whether an individual was enrolled at least once in a housing assistance program within the first 18-months after intake.[13] I use the ELP data to construct economic and social outcomes for the cases in my data. These include, among others, emergency department admissions, mental health services received, and jail bookings and days.[14]

[13]In practice, approximately 60 percent (90 percent) of housing assistance program enrollments occur within the first six-month (year) after intake, and my results are robust to using different time horizons to define treatment.

[14]Each agency has somewhat different time periods coverage, affecting my sample sizes when considering different outcomes. See Appendix B for more details.

3.2 Construction of Instrument and Estimation Samples

I construct two samples of homeless cases to implement the case-worker random assignment design. The instrument sample contains all intakes handled by case workers. I construct it for the purpose of measuring a case worker's share of cases handled that ended up receiving housing assistance, which serves as the instrument for housing assistance receipt. I then impose restrictions on the instrument sample to create the estimation sample which contains all intakes that were as-good-as-randomly assigned to case workers.

I impose several sample restrictions on the intakes data to construct my instrument sample. First, I focus my attention on intakes conducted in 2016-2017, to be able to follow all cases for a period of up to 18 months after intake. Next, I restrict my attention to individuals age 25-65, since individuals who are not in this age group are not considered single adults (under 25 years old) or might have different needs compared to seniors (individuals older than 65 years old). Next, I remove individuals with missing information on case worker, organizational affiliation, or intake location. Following that, I remove duplicates or assessments for the same individual that were conducted on the same day by different case workers. Finally, I remove veteran cases from my sample since homeless veterans are redirected to the United States Veterans Administration Homeless System for further treatment, and hence their case worker assignment is not relevant to whether they receive housing assistance.[15]

I impose two additional restrictions to set up the estimation sample. These restrictions ensure that I consider cases that are as-good-as-randomly assigned to case workers and that the instrument I use in my research design, case workers' housing placement rate, is informative of case workers' propensity to place individuals in housing programs. Specifically, I restrict my attention to service sites that had at least two case workers working in each month and case workers who handled at least 15 cases in 2016-2017.[16] Appendix B.3 describes the steps above in more detail, and Table B.2 shows how the various restrictions affect the number of cases, clients, case workers and service sites in my sample.

3.3 Descriptive Statistics

I first verify that the observed characteristics of cases in my estimation sample are representative of the overall sample of cases. I then investigate the typical patterns of housing assistance and recidivism to homelessness of the individuals in my data. I find that individuals who

[15]This fact was also verified in multiple interviews with service providers and representatives from the Los Angeles Homeless Services Authority (LAHSA).

[16]In Section 5.4, I show that my results are robust when excluding case workers with a relatively small number of cases. I chose the threshold of 15 cases in order to increase sample size and given that case workers handle 25 cases on average at any point in time, with the average duration of a case more than one year, which makes 15 cases a reasonable number in this setting.

receive housing assistance are more likely to return to homelessness in the future compared to individuals who do not, consistent with potential negative selection into housing assistance.

The cases in the estimation sample generally have similar characteristics to those of the overall sample of non-veteran cases. Table B.3 documents the key characteristics of the sample of cases I use in my estimation sample (column 1), non-veteran cases that were handled by case workers in 2016-2017 (column 2), and the cases that were excluded from the estimation sample but are included in the instrument sample (column 3). The typical case in my estimation sample represents an individual with an average age of 45 years old, less likely to be a woman (34 percent of overall sample), more likely to be black (51 percent of overall sample), followed by Hispanic and white, with 23 and 20 percent of the overall sample, respectively. Moreover, 72 percent of cases represent individuals who experienced homelessness in the past. Additionally, 61 percent of cases report chronic homelessness (defined as having a long history of homelessness and a physical disability or serious mental illness), and only 35 percent have used homeless services in the year before assessment. Additionally, the average acuity score, which is the result of the standardized assessment conducted by case workers during intake and indicates the level of needs an individual requires, is 7.3 (out of 17), with a score above 8 indicating high acuity. Finally, as can be seen in the last panel of Table B.3, only 10 to 35 percent of cases have reported using homeless or public services in the past year.

Figure 1 shows the distribution of treatments received for homeless cases in my data. I consider a treatment as enrollment in any housing or non-housing program that occurred in the 18-month period after intake.[17] For simplicity, I show the most intensive service received by the individual. Among the 39,119 non-veteran assessments conducted in 2016-2017, approximately 65 percent of cases received some form of assistance, with about fifty percent of cases receiving housing assistance. In particular, among the cases that received housing assistance, 60 percent received only temporary housing assistance, and the other 40 percent received some type of permanent housing assistance. Less than 5 percent of all cases received permanent supportive housing, the most intensive housing assistance treatment available.

Figure 2 documents the typical recidivism to homelessness patterns for individuals in the instrument sample. For the purpose of my analysis, I define recidivism to homelessness as an

[17] I define treatment in that way for two reasons. First, waiting times for housing programs are usually very long, implying that the time passed from intake to housing placement can be long as well. Second, I do not observe whether a housing placement is linked directly to the case worker handling the individual during intake, and I take the relaxed assumption that any observed housing placement post-intake is due to case worker involvement to some extent. I have tried limiting the treatment time window to 1-month, 3-months, 6-months, and 12-months after intake, and my results do not materially change. I do not count multiple treatments, but my analysis accounts for the number of days the client received housing assistance and the type of housing program (temporary or permanent) in which the client enrolled in Section 5.3.

enrollment in a street outreach program, implying the individual is currently residing in a place not meant for human habitation, or a new intake process, indicating that the individual has returned to seek assistance from the homeless response system.[18] The figure plots the probability an individual returns to the homeless support system at least one time per month in each of the 36-months surrounding the assessment date.[19] There are separate lines for cases that received any housing assistance in the 18 months following assessment and those that did not.

Figure 2 is consistent with the idea that there is potential negative selection into housing assistance treatment. It shows that individuals who receive housing assistance are more likely to interact with the homeless support system prior to their assessment. It reveals that both type of individuals start with a low probability of interacting with the homeless support system (approximately 1 percent), and that these probabilities increase and diverge as the intake date approaches, reaching 13 percent for individuals receiving housing assistance and 10 percent for individuals who did not receive housing assistance in the month prior to intake.

The most striking feature of Figure 2, however, is that individuals who receive housing assistance are more likely to return to homelessness in the post-assessment period compared to those who do not, although this gap becomes smaller over time.[20] The probability of returning to the homeless support system decreases over time for both groups, starting from a high of 12.6 percent and 4.5 percent for individuals receiving housing assistance and those who do not, respectively, to a low of 2.7 percent and 1.7 percent for these two groups after 18 months, respectively.[21] Overall, 52 percent of individuals who receive housing assistance would return to the homeless support system within 18 months from intake, compared to

[18]This measure of recidivism depends to some extent on the behaviors of the homeless individual. One potential story that could lead to an over-estimate is if people who are housed and subsequently return to homelessness feel reluctant to go back to seek assistance because they became discouraged after not receiving the assistance they desired in previous cases. However, in Section 6, I show that individuals who receive housing assistance see improvements in other outcomes such as crime, employment, and health, making this story unlikely to be the case. Alternatively, a person who is denied housing could be more likely to frequently return to seek assistance because they are hoping to get assistance that they did not receive yet. I discuss this possibility in Section 5.1 and show that there is no increase in the probability of housing assistance receipt conditional on returning to the homeless system. Additionally, in Figure B.1, I examine alternative definitions of interactions with the homeless response system. All of them are consistent with my main outcome variable.

[19]Month 0 values are capped at 0.15 for visual purposes since all individuals have a 100 percent probability of returning to the homeless support system in this month by definition.

[20]In Figure B.1, I also show that individuals who receive housing assistance are less likely to report finding a housing solution and are more likely to report going back to the streets or to temporary housing.

[21]There are two main reasons for why recidivism rates are higher in months following intake. First, case outcomes are measured relative to intake date, not relative to housing assistance receipt date, creating a time gap when individuals are not housed and might return to seek assistance. Second, individuals can return to the homeless support system even after receiving housing assistance if they fail to comply with eligibility conditions of housing assistance and leave before assistance has ended, or if their housing assistance has ended and they are back on the streets or seeking more assistance from the system.

only 26 percent among individuals who do not receive housing assistance.

Figure 2 and Figure B.1 motivate my research design. They suggest that using an OLS or an event-study design to estimate the effect of housing assistance on future returns to the homeless support system can lead to biased conclusions, because the group of individuals who receive housing assistance is not comparable to the group of individuals who do not in their pre-intake trends. Moreover, the figures suggest that housing assistance does not prevent recidivism to homelessness. These patterns in the data motivate me to use an instrumental variable research design to address unobserved selection to treatment, which I implement using the random assignment of cases to case workers quasi-experimental approach to identify the causal effect of housing assistance on recidivism to homelessness.

4 Research Design

I exploit the fact that assignment of homeless cases to case workers is as-good-as-random and that case workers differ in their propensity to place clients in housing programs to generate exogenous variation in the probability of receiving housing assistance. I leverage this variation using a leniency ("judge fixed effects") design, which identifies the causal effect of housing assistance on recidivism to homelessness and a large set of economic and social outcomes.

I validate my research design by performing multiple tests for the four required assumptions of the instrumental variable model (exogeneity, relevance, monotonicity, and exclusion) and show that my instrument is consistent with them all. I also document that the average complier is representative of the average case in my sample, although slightly less likely to have physical disabilities or serious mental illness, or to experience chronic homelessness.

4.1 IV Model

I model the relationship between housing assistance and outcomes using an instrumental variable design. My first stage uses the case worker share of housing placements in other cases as an instrument for housing assistance receipt in the current case. Specifically, a case worker with a high housing placement rate is more likely to get the client into housing regardless of their situation.

I am interested in the causal effect of housing assistance on subsequent homelessness and a wide array of economic and social outcomes. This can be captured by the regression model:

$$Y_{it} = \beta_t H_i + X_i' \theta_t + \delta_{sm} + \nu_{it} \tag{1}$$

where β_t is the parameter of interest, H_i is an indicator variable equal to 1 if individual i received any type of housing assistance in the 18-month period after assessment, δ_{sm} is a set of fully interacted service site by month of assessment fixed effects, the level at which random assignment to case workers happens, X_i is a vector of individual-level covariates, and Y_{it} is the dependent variable of interest measured at month t after individual i's assessment (e.g., cumulative number of returns to the homeless support system 18 months after assessment).

As shown in Figure 2, the treated versus non-treated groups are not comparable, which raises concerns about selection bias in the OLS estimation of β_t. My research design addresses this concern by exploiting the quasi-random assignment of cases to case workers (conditional on service site and month of assessment) and the fact that some case workers are systematically more likely to place individuals in housing programs. Taken together, this leads to quasi-random variation in the probability an individual will receive housing assistance depending on which case worker they are assigned to. I use this exogenous variation in H_i to draw inference about the causal effect of housing assistance for the homeless.

My main analysis is based on 2SLS estimation of β_t with Equation (1) as the second stage equation and a first stage equation specified as:

$$H_i = \gamma Z_{j(i)} + \rho_{sm} + X_i^{'}\psi + \varepsilon_i \tag{2}$$

where the scalar variable $Z_{j(i)}$ denotes the housing placement rate of case worker j assigned to individual i's case. Under the assumption of instrument exogeneity and monotonicity, the 2SLS estimand can be interpreted as a positive weighted average of the causal effect of housing assistance among the subgroup of individuals who could have received a different housing assistance treatment had their case been assigned to a different case worker.

One might be worried about exactly how to measure the case worker housing placement rate $Z_{j(i)}$ and perform statistical inference. For my main specification, I measure $Z_{j(i)}$ as the leave-out mean housing assistance rate which omits case i, that is, the average housing assistance rate in other cases the case worker has handled. In Section 5.4, I show robustness to alternative measures of $Z_{j(i)}$, including a veterans-included placement rate and a split sample approach. I also verify the conclusions do not change if I exclude case workers with relatively few cases, change the level of fixed effects, or change the definition of treatment.

In most of my analysis, I perform 2SLS estimation of equations (1) and (2) using the entire sample of all individuals in quasi-randomly assigned cases. However, due to data limitations, and in order to interpret the results and inform policy, I estimate the effect of housing assistance for different subsamples and explore the heterogeneous effects of housing assistance along a variety of dimensions. When exploring outcomes using my administrative records, I can only use early assessments since the end date of many of these records covers less than 18 months after assessment.[22] Additionally, I explore heterogeneous treatment effects by estimating the 2SLS model separately by subgroups. Finally, I explore heterogeneity in effects according to unobservables by estimating the marginal treatment effects and use them to learn about the average treatment effect, the average treatment effect on the treated and the average treatment effect on the untreated.

4.2 First Stage

Case worker's housing placement rate in other cases handled is a strong predictor of housing assistance receipt in the current case, satisfying the relevance (first stage) assumption of the IV model. Specifically, being assigned to a case worker with a 10-percentage point higher housing placement rate increases the probability of housing assistance receipt by 6.4 percentage points.

Figure 3 shows the identifying variation in my data by providing a graphical representation of the first stage. The histogram in the background of the figure shows the distribution of my instrument (controlling for fully interacted service site by month of assessment fixed effects and individual-level covariates). The mean of the instrument is 0.51 with a standard deviation of 0.09. The histogram reveals a large variation in a case worker's tendency to place individuals in housing programs. For example, a case worker at the 90th percentile places about 61 percent of cases in housing programs compared to approximately 41 percent for a case worker at the 10th percentile. Figure 3 also plots the probability that clients receive housing assistance as a function of whether they are assigned to a case worker with a high or low housing placement rate. The graph is a flexible analog to the first stage equation in Equation (2), plotting estimates from a local linear regression. The likelihood of receiving housing assistance is monotonically increasing in the case worker housing placement rate instrument and is close to linear.

Table 2 reports first stage estimates where I regress a dummy for whether an individual received housing assistance in the current case on the case worker housing placement rate instrument. In column 4, I include fully interacted service site by month of assessment fixed effects and a large set of case-level characteristics. The estimate is highly significant, suggesting that being assigned to a case worker with a 10-percentage point higher overall housing placement rate increases the probability of receiving housing assistance by roughly 6.4 percentage points, compared to a baseline mean of 54 percent.

I found no statistically significant relationship between observable case worker characteristics and their housing placement rates. First, I did not find any statistically significant

[22] Table B.1 provides a summary of the various data sources used in this study, the information contained in them, and the time period they cover.

difference in placement rates based on the case worker's gender or ethnicity. Following that, I examined whether tenure or experience might be connected to different placement rates. Figure B.2 shows that there is no systematic relationship between case worker housing placement rate and the number of assessments the case worker conducted or a proxy for the case worker's tenure, respectively.

I continued my investigation regarding the variation in case workers' housing placement propensities by conducting multiple interviews with homeless service providers in Los Angeles County. All of them emphasized that several case worker unobserved personality traits and skills might be important determinants of housing placement rates. First and foremost, case workers are required to build trust and motivate their clients. This task is challenging because many clients do not trust public institutions and have given up hope that their situation can be improved. Moreover, case workers serve as their clients' point of contact and advocates, assisting them in applying to programs and services, following up on their situation, and intervening if there are any problems or modifications to their case plan. The second important characteristic of case workers is their ability to find the relevant services and funding that the client could get in the shortest time possible. This skill requires extensive knowledge of the homeless support system and good networking skills with other service providers and landlords, which could get their clients to the "front of the line" for services that are in short supply, especially housing.[23]

Bearing in mind that there could be many reasons for why some case workers are more likely to place clients in housing programs compared to others, as long as case workers' assignment to clients is random, these underlying reasons should not matter for the causal interpretation of my analysis.

4.3 Instrument Validity

For my instrument to be valid and interpreted as a local average treatment effect, it needs to satisfy the exogeneity, exclusion restriction, and monotonicity assumptions, in addition to the relevance (first stage) assumption. I perform multiple tests for the four assumptions required for the instrument to be valid. My proposed instrument passes them all.

Instrument Exogeneity. Table 1 presents evidence that case worker assignment is as-good-as-random. Columns 1-2 show results from a regression of any housing assistance receipt in the 18 months following assessment on a variety of individual level covariates measured

[23] For example, if a client is eligible for a permanent housing unit but there are no available units, case workers can use their knowledge and skills to find alternative solutions, such as emergency shelter placement, until a permanent housing unit can be found.

before assessment. It reveals that demographics, homeless history, and past receipt of housing assistance are highly predictive of whether a client will receive housing assistance in their current case. In columns 3-4, I examine whether my measure of the case worker housing placement rate can be predicted by this same set of covariates. This is equivalent to the type of test that would be done to verify random assignment in a randomized controlled trial. I find no statistically significant relationship at the 5 percent level between the case worker's placement rate and the various individual level covariates, either individually or jointly. Moreover, the magnitude of the estimates is an order of magnitude smaller compared to their size in Columns 1-2.[24]

As a second test for instrument exogeneity, columns 1-4 of Table 2 explore what happens if a large set of control variables are added to the first stage regression. If case workers are randomly assigned, pre-determined variables should not significantly change the estimates, as they should be uncorrelated with the instrument. As expected, the coefficient does not change appreciably when demographics, case characteristics, and lagged dependent variables capturing an individual's prior involvement with the homeless support system and other public agencies are included.

Exclusion Restriction. Interpreting the IV estimates as measuring the causal effect of housing assistance requires an exclusion restriction. That is, the housing placement rate of the case worker should affect the individual's outcomes only through the housing assistance channel, and not directly in any other way. The key challenge here is that case workers' decisions are multidimensional, with the case worker influencing receipt of both housing and non-housing services. I present empirical evidence that the exclusion restriction holds (see Section 5.4). In particular, I will show that my estimates do not change appreciably when I augment my baseline model to either control for case worker placement rates in non-housing services or include an instrument for receipt of non-housing services.

Monotonicity. If the causal effect of housing assistance is constant across individuals, then the instrument only needs to satisfy the exogeneity and the exclusion assumptions. With heterogeneous effects, however, monotonicity must also be assumed. In my setting, the monotonicity assumption requires that individuals who were assigned to a case worker with a low housing placement rate and received housing assistance would also receive housing assistance if they were assigned to a case worker with a high housing placement rate. This

[24] The indicator variable for black is the only statistically significant coefficient at the 10 percent significance level. However, the size of this coefficient is 20 times smaller than the size of the same coefficient when housing assistance receipt is used as the dependent variable, implying that the economic significance of this variable on case worker housing placement rate is practically zero.

assumption ensures that the 2SLS estimand can be given a local average treatment effect interpretation, i.e. it is an average causal effect among the subgroup of individuals who could have received a different housing assistance treatment had their case been assigned to a different case worker.

One testable implication of the monotonicity assumption is that the first stage estimates should be non-negative for any subsample. For this test, I estimate the first stage on various subsamples, using the same instrument as before. Results are reported in column 1 of Table C.1. In panel A, I construct a composite index of the characteristics included in Table 1, namely predicted probability of receiving housing assistance, using the coefficients from an OLS regression of the probability of receiving housing assistance on these variables. I then estimate separate first stage estimates for the four quartiles of predicted probability of housing assistance receipt. Panel B breaks the data into three case characteristics, based on their acuity scores (low, medium, and high). Panels C, D, E and F split the sample by homeless history, mental health history, emergency health services history and crime history. Panels G, H, I and J split the sample by age, gender, race, and ethnicity. For all these subsamples, the first stage estimates are positive and statistically different from zero, consistent with the monotonicity assumption.

A second implication of monotonicity is that case workers should have a high housing placement rate for a specific case (e.g., history of mental health) if they have a high housing placement rate in other case types (e.g., no history of mental health). To test this implication, I break the data into the same subsamples as I did for the first test but redefine the instrument for each subsample to be the case worker's housing placement rate for cases outside of the subsample. For example, for the history of mental health subsample, I use a case worker's housing placement rate constructed from all cases except history of mental health cases. Column 2 of Table C.1 lists the first stage estimates using this "reverse-sample instrument" which excludes own-type cases. The first stage estimates are all positive and statistically different from zero, suggesting that case workers who have a high housing placement rate for one type of cases also have a high housing placement rate for other types of cases.

4.4 Characteristics of Compliers

The compliers in my sample are defined as those individuals who would receive a different housing assistance treatment if they were assigned to a different case worker. They constitute about 27 percent of all cases in my sample.[25] While the average complier in the sample is

[25] I follow Dahl et al., 2014 in calculating the share of compliers. I begin by regressing case worker housing placement rate (the instrument) on service site x month of assessment fixed effects and all individual controls. Using the residuals from this regression, I define the highest (lowest) housing placement propensity case

generally representative of the average case, they are less likely to have interacted with the homeless system in the past compared to the always- and never-takers in the sample.

I examine the characteristics of the compliers in my sample relative to the always- and never-takers of treatment. I define always-takers as those who would receive housing assistance even when assigned to the case worker with the lowest housing placement rate. Never-takers are defined as those who do not receive housing assistance even when assigned to the case worker with the highest housing placement rate.[26] Compliers are those whose housing assistance receipt is affected by the random assignment to case workers in my sample.

Table 3 shows summary statistics for the three groups within my estimation sample. The share of compliers in my estimation sample is 27%, the share of always-takers is 26%, and the share of never-takers is 47%. Compliers appear to have similar characteristics to the representative case in the estimation sample, although they are slightly less likely to suffer from disabilities or to interact with the homeless system in the past. In particular, compliers are less likely to have a disability (physical and/or mental), and to be chronic homeless (57% compared to 61% in full sample). Moreover, compliers are less likely to use homeless services (27% compared to 35% in the estimation sample) or to have received housing assistance in the year prior to intake (23% compared to 28% in the estimation sample).

Always-takers and never-takers have higher overall acuity and are more likely to be chronically homeless, have a serious disability, be involved in criminal activity, and use homeless services in the year prior to intake. Interestingly, never-takers are considerably less likely to be black (37% compared to 51% in the estimation sample), while always-takers are considerably more likely to be females (44% compared to 34% in the estimation sample).

Overall, the complier analysis of cases suggests that compliers are slightly more likely to be individuals experiencing homelessness who have not been receiving services from the homeless system in the past, and therefore might be more able to take advantage of housing assistance programs, compared to individuals with higher acuity or a long history of homelessness who interact with the homeless system more frequently.

workers as those in the top (bottom) 2.5 percentile of the residuals' distribution. I then run the first-stage regression on the entire sample (i.e., regressing housing assistance receipt on case worker placement rate), and then compute the share of compliers as the product of the first-stage coefficient of the instrument and the difference between the high and low residual case worker housing placement rate.

[26] Since case worker housing placement rate is a continuous variable, I define the 2.5 percentile and the 97.5 percentile of the case worker housing placement distribution as the threshold of the strictest and most lenient case worker, respectively.

5 Main Outcome: Recidivism to Homelessness

I provide evidence that housing assistance prevents and reduces recidivism to homelessness, with a strong impact detected both while and after being enrolled in a housing assistance program. I investigate and conclude that the positive correlation I observe between housing assistance and recidivism to homelessness is a result of non-random assignment into treatment based on unobservables.

Following that, I proceed to document heterogeneous effects by individual and program characteristics. First, I show that individuals with physical disabilities and/or severe mental illness see larger reductions in recidivism rates. Second, I find that the effect of housing assistance on recidivism is driven by placements in permanent housing programs and that the effect of housing assistance on recidivism increases in magnitude as the duration of housing assistance receipt increases.

5.1 Main Results

Housing assistance significantly discourages future returns to the homeless support system. There is a large post-treatment effect, indicating that the effect is not driven solely by the ability to maintain housing while actively receiving assistance. Furthermore, the difference between OLS and IV estimates is driven by selection into treatment based on unobserved characteristics that increase the likelihood of recidivism to homelessness.

Return to Homeless System Probabilities. Figure 4 graphically presents IV estimates of the effect of housing assistance receipt on the probability of returning to the homeless support system.[27] The graph presents a series of cumulative monthly estimates from 1 month to 18 months after assessment. For example, the estimate at month 6 uses the probability an individual has returned to seek services from the homeless support system at least once by 6 months after assessment as the dependent variable in the second stage of the IV model. All of the IV estimates are negative and statistically significant. As expected, the coefficients increase in magnitude over time, since there is more time to return to the homeless support system as time after assessment increases. The estimates suggest that at around 18 months

[27]It is important to emphasize that I do not observe whether a client is homeless at any given point in time, only whether the client has returned to the homeless system. My recidivism measure addresses this measurement issue by including new enrollments in street outreach programs in addition to new intakes. Since street outreach workers actively seek homeless individuals on the streets, implying that the recidivism measure includes both individuals who actively return to the homeless system and individuals who were tracked by the homeless system. However, some individuals may refuse to get services or may not be located by street outreach workers, but may still return to homelessness. My analysis implicitly assumes that case worker assignment is not correlated with these possibilities.

after assessment there is a large and statistically significant reduction of over 20 percentage points in recidivism for those receiving housing assistance.

Comparison to OLS. In Table 4, I present OLS estimates of Equation (1) with and without a rich set of controls. The first specification regresses whether an individual has returned to the homeless support system on whether the individual received housing assistance, but includes no other control variables. The OLS estimates are all positive and significant; for example, individuals receiving housing assistance are 24 percentage points more likely to return at least once over the next 18 months. In the next specification I add all of the individual-level controls and the fully interacted set of service site by month of assessment fixed effects. These controls affect the estimates only slightly.

The divergence between the OLS estimates and the IV estimates is stark. The OLS estimates are always positive, while the IV estimates are negative and large. One possible explanation for this difference is that the average causal effect for compliers differ in sign compared to the mean impact for the entire population. To explore this possibility, I follow Bhuller et al. (2020) and characterize compliers by their observable characteristics. I begin by splitting my sample into eight mutually exclusive subgroups based on acuity score (above and below median) and the predicted probability of receiving housing assistance (see Table C.2). The predicted probability of receiving housing assistance is a composite index of all of the observable characteristics, while acuity score is a potentially key source of heterogeneity in effects. Next, I estimate the first stage equation (2) separately for each subsample and calculate the proportion of compliers by subgroup. I then reweight the estimation sample so that the proportion of compliers in a given subgroup matches the share of the estimation sample for the subgroup. The third row of Table 4 presents OLS estimates based on this reweighted sample. The results suggest that the differences between the IV and OLS estimates cannot be explained by heterogeneous effects, at least due to case-level observables.

Given that, the only remaining explanation is that the OLS estimates suffer from selection bias due to correlated unobservables. If this is the case, I can conclude that the positive rates of recidivism among homeless individuals receiving housing assistance is due to selection, and not a consequence of housing assistance receipt in itself.

Treatment versus post-treatment effect. The recidivism effect in Figure 4 can be decomposed into two components, the ability to maintain housing while actively receiving housing assistance and the ability to maintain housing after housing assistance has ended.[28]

[28] Individuals may return to homelessness while actively receiving housing assistance, as they can fail to comply with eligibility requirements of housing programs or have difficulties in adjusting to being housed.

In Table C.3, I present quarter-by-quarter estimates for returns to the homeless support system in a particular quarter. In Table 4, I group the first and last 9 months together for increased precision. Both tables reveal sizable reductions in recidivism to homelessness, across all periods considered, consistent with a reduction in recidivism to homelessness that is not driven solely by the effect of maintaining housing while actively receiving housing assistance.

In panel (a) of Figure 5, I plot a series of IV estimates for the probability of receiving housing assistance, 1 to 18 months after assessment. Additionally, I plot the share of individuals actively receiving housing assistance in a given month among the individuals receiving housing assistance in the 18-month period after intake. The figure is similar to a survival function, in that if all treated individuals started receiving housing assistance in month 1, the estimates would map out 1 minus the probability of exiting housing programs.[29] As expected, the probability of receiving housing assistance for those who received housing assistance within 18 months after assessment starts out high. This probability falls over time, and becomes somewhat flat around 10 months with about 20 percent of treated individuals enrolled in a housing program.

The main takeaway from panel (a) of Figure 5 is that the effect of housing assistance on recidivism that is driven by maintaining housing while actively receiving housing assistance goes down over time as fewer and fewer treated individuals receive housing assistance. Using this insight, I now graph the probability of ever returning to the homeless support system between months 10 and 18 in panel (b) of Figure 5. By ignoring returns that happened in the first 9 months after assessment, I am estimating housing assistance effects that are less likely to be attributed to the ability to maintain housing while actively receiving housing assistance. I find that the effect is statistically significant and increases in magnitude as time from assessment increases, such that there is a 20-percentage reduction in returning at least once to the system between months 10 and 18 after assessment.[30]

One concern regarding whether the suggested post-treatment effect is real is the possibility is that prior receipt of housing assistance impacts the probability of receiving housing assistance in the future if the case is assigned to another case worker upon completion of the first housing program or if the individual returns to seek assistance from the homeless support system in the hope of getting additional housing assistance. To explore this possibility, in Table C.4, I examine whether case worker housing placement rate in the current case affects housing assistance receipt for new cases of the same individual. I first estimate how housing assistance in the current case affects the probability of receiving housing assistance in another

[29] It is not exactly a survival function because not all individuals receiving housing assistance begin receiving it in month 1 due to waiting times for an open space.

[30] I cannot rule out completely the possibility that the effect I find is driven by those 20 percent of individuals who are still housed even 18 months after assessment.

case in the future. I find a positive and insignificant effect of 1.3 percentage points. The insignificant effect on future housing assistance helps interpret the mechanisms behind my main estimates. In particular, they suggest that a mechanical effect from receiving housing assistance in future cases does not explain the large and persistent reduction in recidivism.

Number of returns to homeless support system. A comparison of Figure 4 and panel (b) in Figure 5 suggests that housing assistance not only prevents an individual from returning to the homeless support system (the extensive margin), but it also prevents individuals from returning multiple times to seek support from the homeless support system (the intensive margin). To further explore the intensive margin response, panel (a) of Figure 6 plots IV estimates for the cumulative number of returns to the homeless support system in the months after assessment. The estimated effects become more negative over time. After 18 months, the estimated effect of housing assistance is around .56 fewer returns, compared to a baseline mean of .72 returns.

Potential returns to the homeless system. The IV estimates represent the average causal effects for compliers who could have received a different housing assistance treatment had their case been assigned to a different case worker. To better understand this LATE, I follow Imbens and Rubin (1997), Dahl et al. (2014) and Bhuller et al. (2020) in decomposing the IV estimates into the average potential outcomes if the compliers would have received housing assistance and if they would not have received housing assistance. The top line in panel (b) of Figure 6 is the number of potential returns to the homeless support system if the compliers would not have received housing assistance. The line trends upward in a close to linear fashion, with approximately 0.6 returns on average after 18 months. In sharp contrast, the compliers would have returned fewer times to the homeless support system if they would have received housing assistance; by month 18, they would only have returned less than 0.2 times to the homeless support system.

Panel (c) of Figure 6 plots the distribution functions for cumulative potential returns to the homeless support system as of 18 months after assessment for compliers if they would have received housing assistance in this time period and if they would not have received housing assistance. The difference between the two CDFs when the number of returns is one is around 10 percentage points, which is approximately half the size of the IV estimate graphed in Figure 4 at 18 months. Comparing the CDFs farther to the right (i.e., for a larger number of returns) makes clear that housing assistance is not simply preventing low-risk individuals from returning to homelessness. To see this, suppose that housing assistance caused individuals who would have returned once to not return at all, but that high-risk individuals (those who would return more than once to the homeless support system) were unaffected. In this case, the two lines in panel (c) would lie on top of each other starting at 2 returns. But, in fact, the two lines diverge at one return and lie on top of each other only after 8 returns. For example, approximately 15 percent of compliers would return to the homeless support system more than 2 times if they did not receive housing assistance, whereas only slightly more than 5 percent of compliers would have this many returns if they received housing assistance. Taken together, the results suggest that housing assistance must be preventing some individuals from returning many times to seek assistance from the homeless support system and stopping some individuals from returning to the homeless support system altogether.[31]

5.2 Heterogeneous Effects: Individual Characteristics

I document heterogeneous effects of housing assistance receipt on recidivism to homelessness by individual characteristics. I begin by showing that the estimated effect for individuals experiencing homelessness for the first time is similar to the estimated effect for the overall sample of cases. I then show that individuals with higher acuity, i.e., with physical disabilities and/or severe mental illness, see larger reductions in recidivism rates compared to individuals without these disabilities.

First Time Homeless. It is possible that first-time homeless are much more likely to benefit from housing assistance compared to individuals who have been homeless for a long time, since the former group is more likely to have the required skills to maintain housing. To explore this possibility, I limit the sample to first time homeless, defined as individuals who have not been previously assessed by a case worker and have not received services from the homeless support system in the past. Table C.5 reports results analogous to Table 4 for this subsample. The 18-months cumulative estimates in column 3 are smaller for first time users of the system, with the estimated reduction in the probability of recidivism lower by 5 percentage points compared to the main recidivism result.

Looking at first time users is useful not only for exploring heterogeneous effects, but also for ease of interpretation. In my estimation sample, individuals can appear more than once if they have multiple intakes over time. These individuals can be in the housing assistance group in one case and the no-housing assistance group in another. With first-time users of the homeless support system, each individual appears only once in the sample. The cost of

[31] From the graph, one cannot infer whether an individual with 3 returns reduces their returns to 0 versus whether an individual with 3 returns reduces their returns to 1 while the individual with 1 return reduces their returns to 0. But the shapes of the CDFs do imply that high-risk individuals (in terms of risk of returning to the homeless support system) must reduce their number of returns.

looking only at an individual's first interaction with the homeless support system is that the sample drops by 44 percent, from 26,752 to 15,146. Given the results are qualitatively similar but with less precision for the smaller sample, I focus on results using the more comprehensive dataset which contains all cases with random assignment.

Heterogeneous effects by observed case characteristics. Table C.6 presents OLS and 2SLS estimates stratified by observable individual characteristics. Differences in IV results are suggestive of differential impacts of housing assistance on the propensity to return in the future to the homeless support system.

My first result implies that individuals who are more likely to receive housing assistance based on their observed characteristics seem to benefit more from it. In panel A, I split the sample by the predicted probability of receiving housing assistance.[32] I split the sample by being above or below the median of this composite index based on all observables. The OLS estimates suggest that individuals below median propensity of receiving housing assistance are similarly likely to return to the homeless support system compared to those with above median propensity of receiving housing assistance. However, the 2SLS estimates show a different picture, with a reduction of 22 percentage points in recidivism probability for individuals with above median propensity for receiving housing assistance, compared to a reduction of 17 percentage points in recidivism probability for individuals with below median propensity for receiving housing assistance.

Consistent with the findings in panel A, I find that the effect of housing assistance on recidivism into homelessness is larger in magnitude for those who have higher acuity score, have a physical or mental disability, and are older. In particular, I find that individuals who belong to one or more of these groups (i.e., high-acuity individuals) have approximately twice as large an effect in terms of the reduction in probability of returning to the homeless support system. These characteristics are highly predictive of whether an individual receives housing assistance, suggesting that individuals who are generally prioritized for housing assistance are more likely to benefit from it.

Marginal Treatment Effects. I follow Bhuller et al. (2020) and explore heterogeneity by examining marginal treatment effects (MTEs) to explore whether unobserved case characteristics play an important role in the effect of housing assistance receipt on recidivism to homelessness. I model the observed outcome as $Y = H \times Y(1) + (1 - H) \times Y(0)$, where H is an indicator for treatment (housing assistance receipt) and $Y(1)$ and $Y(0)$ are the associated

[32] I compute the predicted probability of housing assistance receipt using a probit model where the dependent variable is whether an individual received housing assistance or not on all individual-level characteristics and fixed effects I include in my baseline specification.

potential outcomes which are a linear function of both observable (X) and unobservable factors. The choice of treatment by a case worker is given by $H = 1[\nu(X, Z) - U]$, where ν is an unknown function, U is an unobserved continuous random variable, and Z is the case worker housing placement rate. One can normalize the distribution of $U|X = x$ to be uniformly distributed over $[0, 1]$ for every value of X. Under this normalization, $\nu(X, Z)$ is equal to the propensity score $p(X, Z) \equiv P[H = 1|X = x, Z = z]$.

The MTE is defined as $E[Y(1) - Y(0)|U = u, X = x]$. The dependence of the MTE on U for a fixed X reflects unobserved heterogeneity in treatment effects, as indexed by a case worker's latent propensity to place individuals in housing programs (where U captures unobserved characteristics of the client which influence the case worker). The choice equation implies that, given X, clients with lower values of U are more likely to receive housing assistance regardless of their realization of Z. Following Bhuller et al. (2020), I assume separability between observed and unobserved heterogeneity in treatment effects. Together with the assumption of an exogenous instrument that satisfies monotonicity, this restriction on the potential outcomes is sufficient to allow point identification of MTE over the unconditional support of the propensity score $p(X, Z)$.

Panel (a) in Figure 7 graphs the propensity score distributions to the treated and untreated samples. The dashed red lines indicate the upper and the lower points of the propensity score with common support (after trimming 1% of the sample with overlap in the distributions of propensity scores). Panel (b) of Figure 7 plots MTE estimates by the unobserved resistance to treatment (i.e., the latent variable U) based on a local instrumental variables approach using a global cubic polynomial specification. The MTE estimates are most negative for those with a low unobserved resistance to treatment. This implies that housing assistance reduces recidivism the most for clients whose unobservables would make them more likely to receive housing assistance regardless of the case worker housing placement rate. On the other hand, those whose unobservables would make them less likely to receive housing assistance experience an increase in recidivism due to treatment, noting that the estimates are noisy.

Table C.7 uses the MTE estimates to construct rescaled estimates of the average treatment effect on the treated (ATT), the average treatment effect (ATE), and the average treatment effect on the untreated (ATUT). These weighted averages are obtained by integrating the MTE over the propensity score for the relevant sample. The ATT estimates reveal the recidivism effects of housing assistance are similar to the LATE estimates I find in my IV estimation in Table 4, and the ATE are larger in magnitude, since the ATUT estimates, while still negative, are smaller in magnitude and statistically insignificant. These results suggest that unobserved characteristics reveal that those individuals with the highest likelihood of receiving housing assistance are the ones with the largest response in terms of reduced probability of returning to the homeless support system. However, as the MTEs suggest, the effect of housing assistance is negative for most individuals, suggesting that while there might be variation in treatment effects based on unobserved characteristics, housing assistance does reduce recidivism into the homeless support system for the majority of individuals.

5.3 Heterogeneous Effects: Program Characteristics

I document heterogeneous effects of housing assistance receipt on recidivism to homelessness by program characteristics. I find that the effect of housing assistance on recidivism is driven solely by placements in permanent housing programs. Consistent with this finding, I show that the effect of housing assistance on recidivism increases in magnitude with the duration of housing assistance, and that this result is driven by intensive margin responses (e.g., moving from a 6-days temporary housing program to a 6-months permanent housing program).

Permanent versus Temporary Housing. As a reminder, there are two main types of housing assistance programs for individuals experiencing homelessness in Los Angeles County: permanent and temporary. As described in Section 2.2 and in Appendix A, permanent housing programs connect individuals to permanent housing which they are expected to keep after housing assistance has ended, while temporary housing programs provide temporary shelter for individuals until they can solve their homelessness problem or until space in a permanent housing program becomes available. Whether an individual receives temporary or permanent housing assistance depends on the acuity of their situation and the availability of beds/units.

Case workers are able to influence the type of housing assistance an individual receives, and indeed some case workers place more individuals in permanent housing programs compared to others. I examine whether my case worker housing placement rate is also capturing differences in the quality of housing placements, where I consider permanent housing assistance to be of higher quality compared to temporary housing assistance. To explore this possibility, I run a multinomial regression with three outcomes (received permanent housing assistance, did not receive permanent housing assistance but received temporary housing assistance, did not receive housing assistance), and I find that being assigned to a case worker with a higher housing placement rate increases the probability of receiving permanent housing assistance.[33] In addition, in Table C.8, I run first-stage-like regressions where I regress permanent (temporary) housing receipt on case worker housing placement rate, and find that the first-stage coefficients are positive and statistically significant. However, I cannot reject

[33]In a multinomial logit regression, case worker housing placement rate has an average marginal effect of .317 (s.e. .028) for permanent housing assistance versus .192 (s.e. .038) for temporary housing assistance, with no housing assistance being the omitted category.

the hypothesis that they are equal.

To explore whether individuals receiving temporary versus permanent housing assistance experience different outcomes, I construct two instruments for temporary and permanent housing assistance receipt in a similar fashion to my original instrument. Specifically, I construct two housing placement rates for each case worker, one for permanent housing placements and the other for temporary housing placements. The sum of these two instruments gives the original housing placement rate instrument.[34]

In Table 5, I re-estimate my main IV specification, but with the two separate endogenous variables and instruments described above. I find that individuals who received permanent housing assistance treatment are 31 percentage points less likely to return to the homeless support system within 18 months compared to individuals who received no housing assistance, while individuals who received temporary housing assistance treatment are only 2.3 percentage points less likely to return to the homeless support system within 18 months compared to individuals who did not receive housing assistance, and that this effect is statistically insignificant. This result suggests that programs that help connect an individual to permanent housing, essentially exiting them from homelessness by securing a long-term housing solution, are more effective in preventing future returns to the homeless support system. However, these programs are more costly, and I address the question of whether they are cost effective in Section 7.

Duration of Housing Assistance It is possible that case workers with a higher propensity to place individuals in housing programs are also more likely to place their clients in programs with a longer duration. If this is the case, my baseline estimates capture a linear combination of the extensive margin effect of receiving housing and the intensive margin effect of housing assistance duration. As shown in Figure C.1, the median duration of housing assistance is about 100 days in my sample, with roughly 85% of housing assistance duration being less than one year. Empirically, there is significant variation in duration of housing assistance across case workers, even when holding housing placement rates fixed. This is consistent with the hypothesis that case workers' influence is mostly through connecting individuals to housing programs and only slightly influence the duration of assistance.

I explore various models which use duration of housing assistance. To provide context, panel (a) of Figure C.2 graphs housing assistance duration in days (including zeros) as a function of my case worker housing placement rate. Panel (b) illustrates how duration of housing assistance is affected by my instrument. It plots estimates of the probability that the duration of housing assistance will exceed a given number of days (including zeros) as

[34]Table C.9 presents the corresponding balancing tests for these instruments.

a function of the case worker housing placement rate instrument, and reveals that a case worker's placement rate effect on the number of days is larger for shorter duration spells and decreases as duration of housing assistance increases.

A complementary analysis is to replace the endogenous variable of housing assistance receipt with duration of housing assistance, but still use my case worker housing placement rate as the instrument. As shown by Angrist and Imbens (1995), 2SLS applied to an IV model with variable treatment intensity (such as duration of housing assistance in days) captures a weighted average of causal responses to a unit change in treatment, for those whose treatment status is affected by the instrument. The weight attached to the jth unit of treatment is proportional to the number of people who, because of the instrument, change their treatment from less than j to j or more. In my setting, this means that defining the endogenous regressor as duration of housing assistance in days permits identification of a weighted average of the effect of another day of housing assistance. Thus, this parameter captures a convex combination of the extensive margin effect of receiving housing assistance and the intensive margin effect of longer duration. When estimating this model with days of housing assistance as the endogenous regressor, the results are consistent with those using the binary housing assistance measure. The effect of increasing the duration of housing assistance by 250 days (the average housing assistance duration implied by the instrument for individuals receiving housing assistance), yields estimates which are similar in size to my estimates based on the binary endogenous variable of housing assistance (see Table C.10).

Finally, I consider models which include both housing assistance receipt and duration simultaneously. My first exploration is what happens if I control for a case worker's housing assistance duration rate, defined as the average duration of housing assistance in other cases the case worker has handled. In Table C.11, Panel C, when I add in controls for housing assistance duration rate, the first stage estimate is slightly reduced but the IV estimates are reduced by about half and are no longer statistically significant. This result is due to the high correlation between the case worker housing placement rate and the case worker housing assistance duration rate. In Table C.12, I treat both housing assistance receipt and duration as endogenous variables and use the case worker housing placement and housing assistance duration rates as the two instruments. I find that all of the effect on recidivism can be attributed to the duration of housing assistance received (intensive margin) and that there is no effect on recidivism for the extensive margin, suggesting that longer housing assistance spells are driving reductions in recidivism into homelessness, consistent with my result that the effect of housing assistance on recidivism is driven by permanent housing programs.

5.4 Robustness

Specification Checks. Table C.13 examines the sensitivity of my results to alternative minimum case worker assessments required for inclusion in my estimation sample. Column 1 presents my baseline results, which include any cases whose case worker handled at least 15 cases in 2016-2017. In the next four specifications, I instead require case workers to handle at least 10, 20, 30, or 40 cases, respectively. These changes do not materially affect the estimated effects. This is reassuring, as one might be worried the statistical inference becomes unreliable if the number of cases per case worker is too small.

Table C.14 examines the sensitivity of my results by allowing the fixed effects within which time period and site are compared to vary. Column 1 presents my baseline results, where case worker assignment is random conditional on service site by month of assessment, for comparison. In this specification, I include cases from service sites that had at least two case workers working in a given month. In the next two specifications, I instead require at least two case workers working in the same site in a given quarter and year, respectively. In columns 4 and 5, I change the sample criteria and require that at least two case workers working in the same month for the same service provider (who might operate several service sites) and in the same Service Planning Area of Los Angeles County (which have different service providers operating in them), respectively.[35] These different selections of the level at which cases are compared are not different from the estimated baseline effects. This is reassuring, as one might be worried the cell sizes used in my estimation sample might be too small and thus sensitive to changes in specification.

Table C.15 examines the sensitivity of my results to the definition of treatment. Column 1 presents my baseline results, where housing assistance treatment is defined as being enrolled in any housing assistance program within 18 months after assessment date. In the next four specifications, I instead require that enrollment to housing assistance programs occurs within 1 month, 3 months, 6 months, and 12 months after assessment to be considered as treated, respectively. One limitation of my data is that I cannot observe if a placement in a housing program is directly linked to the case worker. As a result, I face a trade-off when deciding what the relevant time period is to consider whether the case worker's involvement was relevant for the housing placement. The closer the housing placement is to enrollment, the more likely it is that the case worker is directly responsible for it. This fact is verified by observing the first-stage coefficients, which range from 0.86 when treatment window is defined as one month after assessment to 0.64 when treatment window is 18 months after assessment. However, due to the short supply of housing units in Los Angeles County, waiting

[35] There are eight service planning areas (SPAs) in the county of Los Angeles.

times for housing assistance, especially for permanent housing programs, can be exceptionally long, reaching more than a year in some cases. As a result, I could count individuals as untreated due to long waiting times. My estimates suggest that the size of the effect of housing assistance on recidivism to the homeless support system is larger the longer the treatment window is, consistent with longer waiting time for permanent housing placements and larger effects for these type of programs compared to temporary housing programs (see Section 5.3). Yet reassuringly, all treatment definitions suggest that housing assistance receipt reduces recidivism to homelessness.

Table C.16 examines sensitivity to changing how the instrument is constructed. In column 2, I check whether my results are sensitive to outliers by winsorizing the top and bottom 5 percent values of my baseline instrument. In column 3, I randomly split my sample in half and use one half of the sample to calculate the average housing placement rate for each case worker. I next use these measures of case worker housing placement rate as an instrument for housing assistance in the other half of the sample. In column 4, I construct my instrument using all available cases, including veteran cases. I construct the measure in this way in order to verify that veterans' housing placements are indeed orthogonal to case worker assignment. Finally, in column 5, I construct my instrument using a residualized, leave-out case worker housing placement rate that accounts for service site by month of assessment fixed effects. Specifically, I regress housing assistance receipt on fully interacted service site by month of assessment fixed effects and construct a case worker housing placement rate using the residuals obtained from this regression. I construct the measure in this way to address the possibility that there are differences across service sites and over time in availability and policy of providing housing assistance. Across all these different instrument definitions, the resulting estimates (and standard errors) do not materially change.

Threats to Exclusion Restriction As discussed in Section 4.3, interpreting the IV estimates as the average causal effect of housing assistance requires the case worker housing placement rate to affect an individual's outcomes only through the housing assistance channel. A potential issue is that case workers may also affect an individual's receipt of non-housing services that are intended to support the individual's transition out of homelessness. These supportive services include providing meals and showers, health care and mental health treatment, substance abuse treatment, employment, life skills classes and education, and general case management.

To examine the potential impact on individuals' outcomes via non-housing services, I extend my baseline IV model to distinguish between housing assistance and non-housing assistance:

$$H_i = \alpha Z^H_{(j)i} + \gamma Z^S_{j(i)} + \chi_{sm} + \nu_i \tag{3}$$

$$S_i = \tau Z^H_{j(i)} + \psi Z^S_{j(i)} + \lambda_{sm} + u_i \tag{4}$$

$$Y_{it} = \beta_t H_i + \theta_t S_i + \delta_{sm} + X_i^{'} \omega_t + \rho_{it} \tag{5}$$

where j denotes the case worker who handles individual i's case, H_i is an indicator variable equal to 1 if individual i received any housing assistance in the 18 months following assessment, S_i is an indicator variable equal to 1 if individual i received any non-housing assistance in the 18 months following assessment, $Z^H_{j(i)}$ denotes the case worker housing placement rate, $Z^S_{j(i)}$ denotes the case worker non-housing services placement rate, and X_i is a vector of control variables. All specifications include a full set of service site by month fixed effects. The omitted reference category is no assistance received at all. As in the baseline model, I measure $Z^H_{j(i)}$ and $Z^S_{j(i)}$ as leave-out means.

There are two cases in which the baseline IV estimates are biased because they abstract from the case worker's in providing other types of assistance. In the first case, $Z^H_{j(i)}$ correlates with $Z^S_{j(i)}$, and $Z^S_{j(i)}$ directly affects Y_{it} (conditional on fixed effects and individual level covariates). This would violate the exclusion restriction in the baseline IV model because $Z^H_{j(i)}$ not only affects Y_{it} through H_i but also through its correlation with $Z^S_{j(i)}$. However, controlling for $Z^S_{j(i)}$ in both (1) and (2) eliminates this source of bias. In the second case, $Z^H_{j(i)}$ correlates with S_i conditional on $Z^S_{j(i)}$, and S_i affects Y_{it} holding H_i fixed (conditional on fixed effects and individual level covariates). In the baseline IV model, this would violate the exclusion restriction because $Z^H_{j(i)}$ affects Y_{it} not only through H_i but also through its influence on S_i. The augmented IV model (3)-(5) addresses this issue by including S_i as an additional endogenous variable and $Z^S_{j(i)}$ as an extra instrument.

I examine these two cases and find support for the exclusion restriction. The top panel of Table C.11 repeats my baseline specification for comparison. In panel B, I add the case worker non-housing services placement rate as an additional control in both the first and second stages. The IV estimates for both recidivism outcomes are similar to my baseline.

I next estimate the augmented IV model given by (3)-(5). Table C.17 presents the first stage, reduced form, and IV estimates. For the housing assistance first stage, the case worker housing placement rate has a coefficient similar to that in the baseline model. For the other first stage, the case worker housing placement rate has a negative impact on receiving non-housing services, but the other instrument has a large positive effect. Looking at the reduced form estimates, the coefficients on the case worker housing placement rate are virtually unchanged relative to the baseline IV model. Likewise, the IV estimates for housing assistance are similar to those from the baseline model which does not include the instrument for the non-housing services placement.

A useful byproduct of examining the threats to exclusion from case worker effects other than housing placement is that it helps with interpretation. The baseline IV model compares potential outcomes if the individual received housing assistance to the outcomes that would have been realized if they did not. The augmented IV model further distinguishes between no assistance at all and non-housing assistance. The IV estimates show significant effects of receiving housing assistance compared to not receiving any assistance, whereas receiving non-housing services has no effect on recidivism to homelessness.

6 Additional Economic and Social Outcomes

In this section, I present my findings on the effect of housing assistance on a large set of economic and social outcomes. Table 6 presents my main findings. I show that (i) housing assistance causes a reduction in the number of emergency department visits, (ii) a reduction in mental health services received, (iii) a reduction in the number of jail days and the probability of committing a crime, (iv) an increase in the probability of reporting employment, and (v) no effect on receipt of social benefits.[36]

Department of Health Services. In Table D.2, I present OLS and IV estimates of Equation (1) for various outcomes related to Los Angeles County's Department of Health Services (DHS) service utilization. In Panel A, the dependent variable is an indicator equal to 1 if the individual received treatment within 18 months after assessment, and in Panel B the dependent variable is the number of treatments (days) the individual received in the same time period. Column 1 combines all treatment types, while columns 2-4 break treatments into inpatient, outpatient and emergency services, respectively. The IV estimates are negative and significant for overall DHS treatments and for emergency department visits, indicating that housing assistance leads to a reduction in the number of health services received and of emergency department visits in particular. Specifically, there is a 5.4 percentage point drop in the probability of visiting the emergency department and .14 reduction in the number of emergency department visits, although the latter is not statistically significant. Overall, the observed reduction in overall DHS services and emergency department visits suggests that housing assistance helps stabilize an individual's health and also prevents them from being exposed to dangerous and extreme situations which might increase the possibility of physical harm.

[36]In this section, I use subsamples of my baseline estimation sample because of data limitations. Table D.1 verifies that the first stage and recidivism findings I document in the previous sections are valid across all the subsamples I use to explore additional economic and social outcomes.

Department of Mental Health Services. In Table D.3, I present OLS and IV estimates of Equation (1) for various outcomes related to Los Angeles County's Department of Mental Health (DMH) service utilization. In Panel A, the dependent variable is an indicator equal to 1 if the individual received treatment within 18 months after assessment, and in Panel B the dependent variable is the number of treatments (days) the individual received in the same time period. Column 1 combines all treatment types, while columns 2-4 break treatments into acute inpatient, residential and outpatient services. The IV estimates suggest that housing assistance reduces the probability of receiving mental health services in the 18-month period after assessment by 4.6 percentage points, relative to a baseline mean of 7 percentage points. Moreover, the estimates suggest that individuals who receive housing assistance spend 3 days fewer in inpatient or skilled nursing facilities treating mental health, compared to a baseline mean of 3.5 days. This suggests that housing assistance diverts individuals from skilled nursing facilities, which are far more expensive compared to providing housing assistance. In addition, I find that individuals who receive housing assistance see a reduction in outpatient mental health treatments, although this effect is statistically insignificant. Overall, the results suggest that housing assistance receipt leads to a reduction in the probability and number of mental health treatments received, indicating increased stabilization of mental health among housing assistance recipients. Moreover, the decrease in inpatient and residential days in skilled nursing facilities suggest that housing assistance can be a good solution for some individuals with serious mental illnesses who can live on their own but do not have the resources or are facing barriers to housing.

Department of Public Health. In Table D.4, I present OLS and IV estimates of Equation (1) for various outcomes related to the Los Angeles County's Department of Public Health (DPH) service utilization. The Department of Public Health mostly provides substance abuse treatments. In Panel A, the dependent variable is an indicator equal to 1 if the individual received treatment within 18 months after assessment, and in Panel B the dependent variable is the number of treatments (days) the individual received in the same time period. Column 1 combines all treatment types, while columns 2-4 break treatments into detox, residential and outpatient services. The IV estimates suggest that housing assistance reduces DPH outpatient services by 0.11 over an 18-month period, compared to a baseline mean of 0.08. Moreover, there seems to be no relationship between housing assistance receipt and participation in detox or residential programs that assist with substance abuse problems.

Criminal Activity. In Table D.5, I present OLS and IV estimates of Equation (1) for various outcomes related to crime from the Los Angeles County Sheriff's Department (LASD) and the Los Angeles County Probation Department. In column 1, the dependent variable is the number of jail bookings an individual had in the 18-month period after assessment. The OLS coefficient shows that individuals who received housing assistance are more likely to have been in jail during this period. The IV estimates, however, show that there is a significant reduction in the number of jail bookings, with individuals who received housing assistance having 1.5 fewer jail bookings on average compared to individuals who did not receive housing assistance. Column 2 shows that there is a corresponding decline in the number of jail days for individuals who received housing assistance. In columns 3 and 4, the dependent variables are an indicator for whether the individual was charged for a crime at least once and the number of charges during the 18-month period after assessment, respectively. Consistent with the jail results, I find that individuals who received housing assistance were 7.9 percentage points less likely to be charged with at least one crime and were charged with .4 fewer crimes during this period, compared to baseline means of 0.1 and 0.22, respectively. In columns 5 and 6, the dependent variables are an indicator for whether the individual was under probation at least once during the 18 months after assessment and the number of days under probation, respectively. The IV estimates are negative, suggesting that there is a drop in the probability of being under probation; however, this effect is not statistically significant. Taken together, the results on jail bookings, crimes, and probation suggest that housing assistance leads to a reduction in criminal activity, which is translated into fewer jail bookings and days and reduced probability of being under probation.

Employment and Income. The Homeless Management Information System (HMIS) contains self-reported information on income and employment. I use these responses to examine the effects of housing assistance on these outcomes. However, I note that there are two main caveats that require caution when interpreting these results. First, this data is self-reported, as opposed to all other outcomes so far which were based on administrative records. Second, only individuals who are enrolled in a program that is being operated by a service provider in the homeless support system and provide information on employment and income are included in the sample. With that in mind, Table D.6 presents OLS and IV estimates of Equation (1) for employment, income, and social benefits outcomes. In columns 1-2, the dependent variables are an indicator equal to 1 if the individual reported having non-zero income and the individual's reported average monthly income, respectively. The OLS coefficients show that individuals who received housing assistance are also more likely to report non-zero income and also more likely to report a higher monthly income, suggesting that there might be selection on reporting income and employment. The IV estimates show that there is a 26-percentage point increase in the probability of reporting non-zero income and a $442 dollars increase in mean monthly income reported in the 18-month period after assessment for individuals who received housing assistance. In columns 3-4, I find similar results for reporting employment and mean monthly wage. In particular, I find a 24-percentage point increase in the probability of reporting employment and a $430 dollars increase in mean monthly wage for individuals who received housing assistance in the 18-month period after assessment. In columns 5-6, I show that there is no relationship between housing assistance receipt and social benefits receipt. Taken together, the results suggest that housing assistance leads to increased probability of finding employment, and that this increase in income is driven entirely by employment.

Social Benefits. The Homeless Management Information System (HMIS) also contains self-reported information on receipt of various social benefits. I use these responses, in addition to administrative records on receipt of emergency cash assistance from the Department of Public and Social Services (DPSS) to examine the effects of housing assistance on social benefits. For self-reported outcomes, the same caveats and caution outlined for the employment and income data should be taken. In Table D.7, I present OLS and IV estimates of Equation (1) for receipt of different social benefits. In columns 1-4, the dependent variable is an indicator equal to 1 if the individual reported ever receiving emergency cash assistance (General Relief), supplemental security income (SSI), social security disability income (SSDI), and food stamps in the 18-month period after assessment. The OLS coefficients show positive correlation between receiving housing assistance and reporting receipt of these social benefits. On the contrary, the IV estimates show no relationship between housing assistance and social benefits receipt. However, the estimates suggest that there is a reduction in receipt of emergency cash assistance and an increase in reporting of SSI, SSDI, and food stamps receipt, although these are not statistically significant. The reduction in emergency cash assistance combined with increase in other social benefits is consistent with increased housing and income stability. Overall, the results suggest that housing assistance does not seem to affect social benefits receipt, and if anything, reduces it.[37]

[37] One concern is that preexisting employment and income might be influencing housing assistance receipt and the recidivism result I find in the previous section. To explore this probability, I have attempted a version of my baseline model where I treat all future outcomes related to health, crime, employment, income, and social benefits, as controls in a specification where the dependent variable is recidivism into homelessness. I find that the IV estimates are not changed by the inclusion of these controls, suggesting that the effect I find is indeed driven by the housing assistance channel and not other channels.

7 Cost-Benefit Analysis

The most relevant policy implication is whether the positive effects from housing assistance for the homeless I find in this study are cost effective and is there a difference in the cost-effectiveness of different housing program types. It is difficult to estimate the benefits of reductions in homelessness and costs of housing assistance, with the few studies attempting to do so imposing strong assumptions and extrapolations to their computations (Culhane et al., 2002; Evans et al., 2016; Khadduri et al., 2010). I attempt to conduct a simple cost-benefit calculation of housing assistance for the homeless. My calculations suggest that up to 80 percent of housing costs are offset by corresponding benefits in the first 18 months following assessment, and that the benefits tend to be larger in permanent housing programs.

To calculate the costs of housing assistance reported in Table 7, I multiply the number of housing assistance days received for each individual in my sample during the 18-month period after initial assessment by the average cost per day of each program type, such that direct housing costs are set at $35 per day for temporary housing, $40 per day for rapid re-housing, and $50 per day for permanent supportive housing (LAHSA,2017). The IV estimate which uses this outcome measures a cost of $10,366 per housing assistance spell. This measure captures the average cost of housing assistance and not the marginal cost, which I would ideally estimate. In Panel B, I break housing assistance by type (temporary and permanent) and estimate the cost of each using the two instruments I used when estimating the impact of permanent versus temporary housing assistance on recidivism in Section 5.3. The IV estimates measure an average cost of $5,095 per temporary housing spell and an average cost of $12,402 per permanent housing spell.

On the benefits side, I measure four broad categories. First, there is a reduction in homeless support system spending on future housing assistance due to fewer returns to the homeless support system. I compute the savings in housing costs per homeless system return avoided as the average housing assistance cost of an assessment in my sample. Homeless support system average savings in housing assistance costs are estimated to be $4,000 per assessment. I then create an outcome variable which takes the total number of returns to homeless support system in the 18-month period after assessment multiplied by $4,000. Using this measure, I estimate savings of $2,102 per housing assistance spell. In panel B, I estimate savings of $2,885 per permanent housing assistance spell and only an insignificant $558 per temporary housing assistance spell.

The second and third categories of benefits I compute are due to improved health and reduced crime, which are translated to reduction in use of public resources. I use estimates of Los Angeles County on the costs of the various treatments and services I explore in the ELP data. For example, the estimate for a day in jail is \$200 per day. I then define public health costs as the sum of DHS and DMH costs, and law enforcement costs as the sum of jail days and probation months, where I use county estimates multiplied by the number of treatments or occurrences of each type of service. The IV estimates of these savings are \$2,796 for health costs and \$1,724 for law enforcement costs. In panel B, the IV estimates of these savings from temporary housing spell are \$3,214 and \$1,089 for health and law enforcement, respectively, while the estimated savings from permanent housing assistance spell are \$2,085 for health and \$1,746 for law enforcement.

The third category of benefits is due to increased employment and no effect on social benefits receipt that I find in Section 6. I estimate the increase in taxes minus social benefits to be \$1,146 per housing assistance spell. When looking at different housing program types, I estimate savings of \$1,862 per permanent housing assistance spell and \$353 in savings per temporary housing assistance spell. I define net transfers as all social benefits received minus all income taxes paid over the 18-month period after assessment.

Overall, I find that a substantial portion of housing assistance costs are offset by the savings to public agencies in the first 18 months following assessment. I note that these savings are likely to be even larger, as I ignore the indirect benefits from the reduction in street homelessness. Moreover, these benefits are likely to accumulate over time and become larger, since the cost of homelessness increases exponentially with time (Flaming et al., 2015). Finally, I note that these savings tend to be larger in permanent housing programs, consistent with my findings regarding the effect of these programs on recidivism.

8 Conclusions

The ongoing crisis of homelessness has generated a shift towards the Housing First approach, which aims to quickly provide individuals experiencing homelessness with housing assistance without preconditions (Burt et al., 2017). In recent years, researchers and policy makers have questioned whether housing assistance is sufficient to treat homelessness and whether the Housing First approach is cost effective. However, despite the widespread adoption of this policy, the existing literature did not provide robust evidence regarding these questions.

My study fills this gap in the literature using administrative data and exogenous variation in housing assistance receipt to confirm that housing assistance programs for the homeless can indeed reduce recidivism to homelessness, in addition to improving other economic and social outcomes that contribute to improved likelihood of successful rehabilitation and reintegration to society. The Los Angeles County Homeless Support System, despite its lack of resources, is successful in preventing future homelessness and improving important well-being measures when it provides housing assistance to individuals experiencing homelessness.

While this paper establishes these fundamental results, several important questions remain for future research. My results do not imply that housing assistance alone is cost effective for all individuals experiencing homelessness. Exploring additional research designs that will manipulate housing assistance receipt for the always- and never- takers in my sample is important for understanding how to treat this segment of the population with the highest level of needs. Additionally, while I provide some evidence that housing assistance has a beneficial effect on many economic and social outcomes, additional evidence would be useful to assess the external validity of my findings. Finally, the cost-benefit analysis I conducted ignores the most expensive part of housing assistance: acquisition and construction costs. Evidence taking these costs into account, either in a partial- or a general-equilibrium setting would be of great value.

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9 Figures

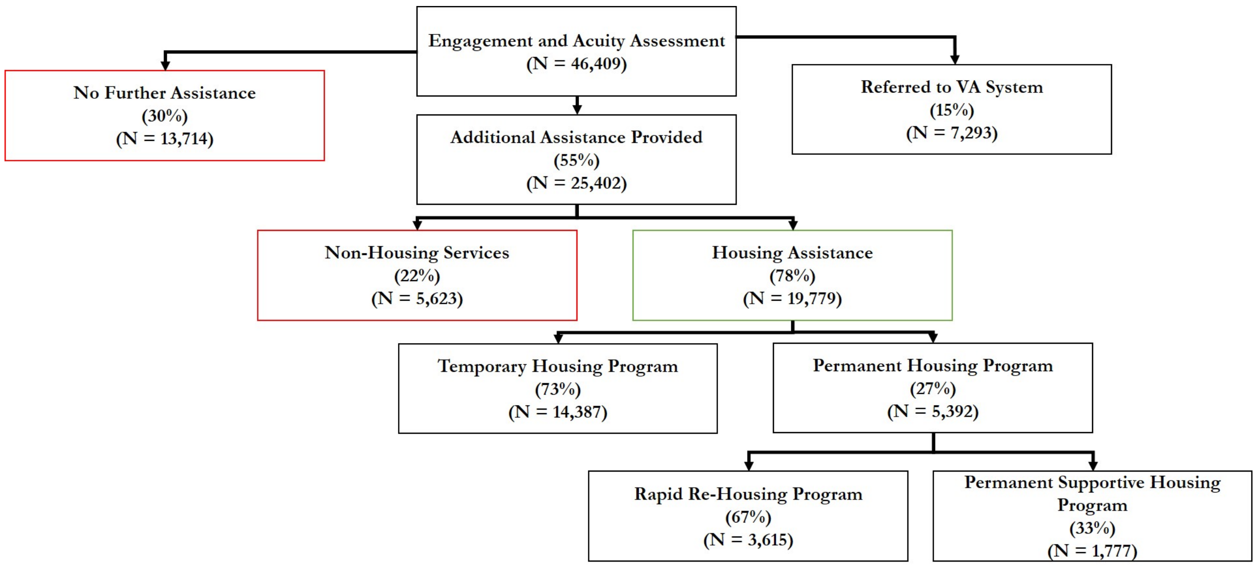


Figure 1. CES Process and Best Treatment Distribution.

Note: The following chart displays homeless case outcomes by best treatment received. The sample consists of all intakes conducted in 2016-2017 for single adults experiencing homelessness by the homeless service providers in Los Angeles County. Treatments received are not mutually exclusive and best treatment received is presented for simplicity. The green and red colored boxes represent the treated non-treated cases in my estimation sample, respectively.

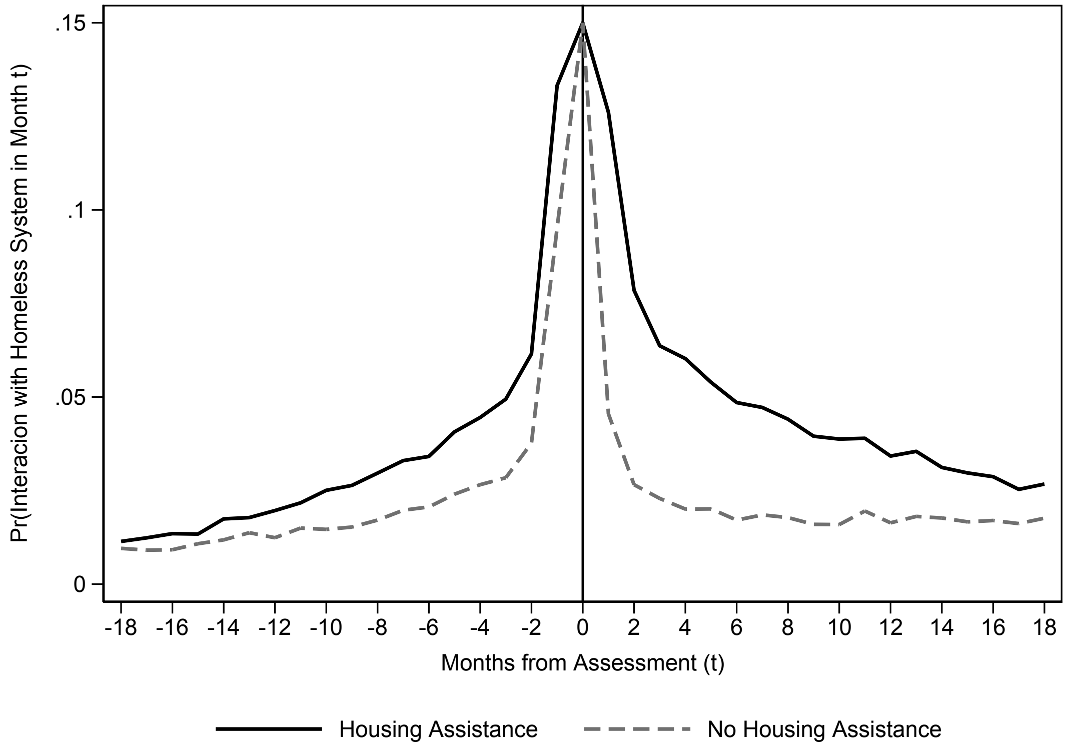


Figure 2. Recidivism into Homelessness Before and After Month of Intake.

Note: Instrument sample consisting of 39,119 non-veteran single adult intakes in 2016-2017. Cases are categorized in two groups, those receiving housing assistance within 18 months from intake date, as shown in solid black, or those not receiving housing assistance within this period, as shown in the dashed grey line. Recidivism into homelessness is defined as enrolling in a street outreach program or being assessed by a case worker at least once in each month. Month 0 outcome is capped at 0.15 for visual purposes (both groups have a probability of 1 in this month by definition).

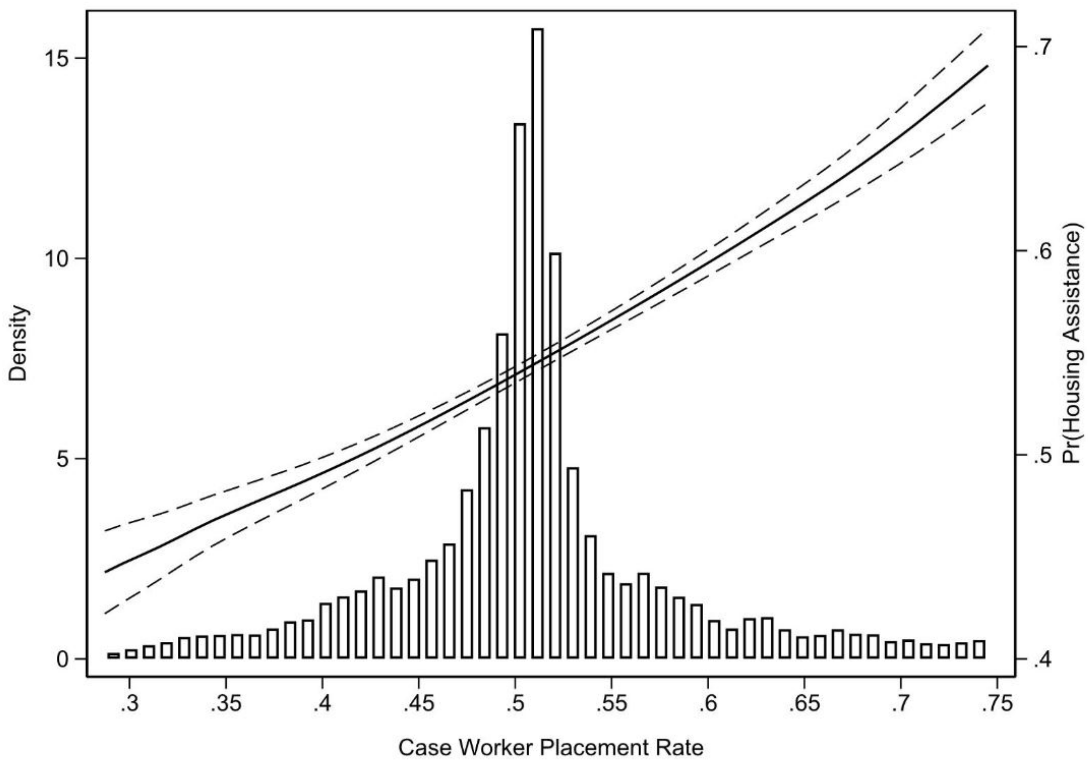


Figure 3. First Stage Graph of Housing Assistance Receipt on Case Worker Housing Placement Rate.

Note: Estimation sample consisting of 26,752 assessments processed in 2016-2017. Probability of housing assistance receipt is plotted on the right y-axis against leave-out mean case worker housing placement rate of the assigned case worker shown along the x-axis. The plotted values are mean-standardized residuals from regressions on site x assessment month fixed effects and all variables listed in Table 1. The solid line shows a local linear regression of housing assistance receipt on case worker housing placement rate. Dashed lines show 95% confidence intervals. The histogram shows the density of case worker placement rates along the left y-axis (top and bottom 2% excluded).

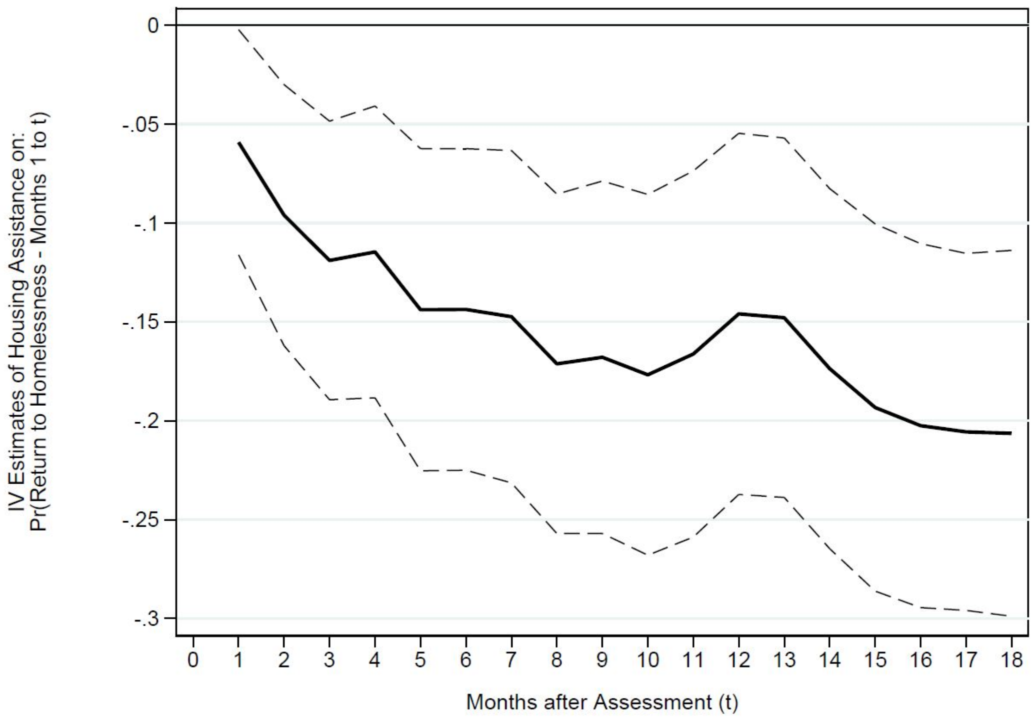
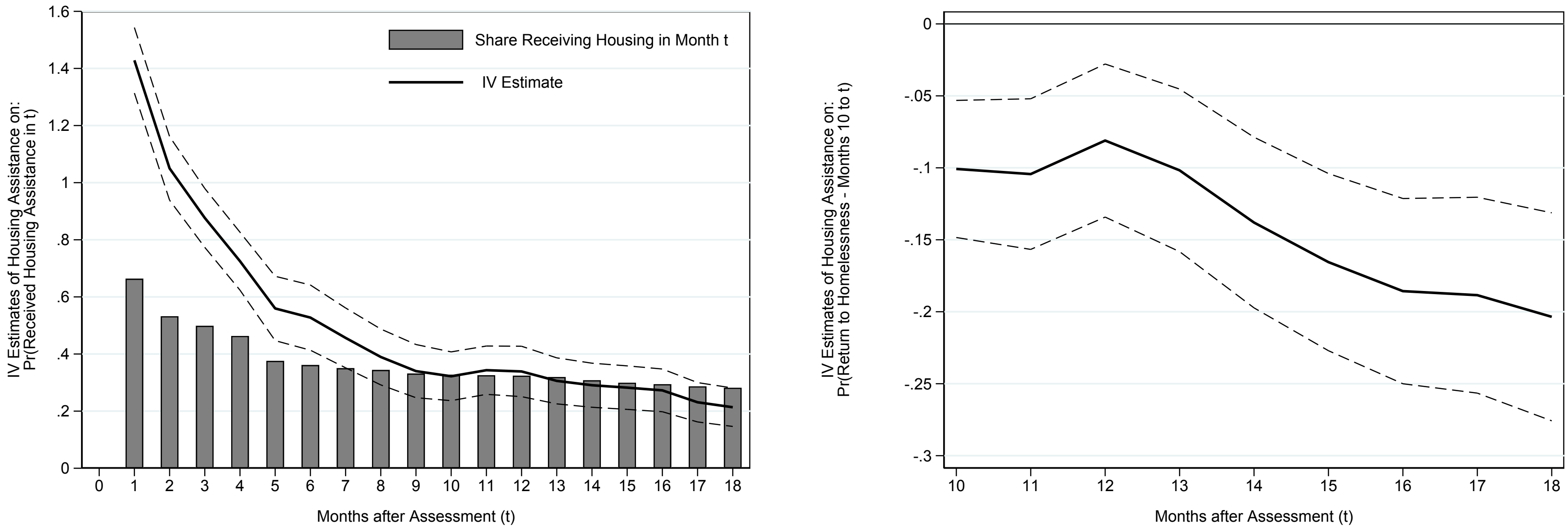


Figure 4. The Effect of Housing Assistance on Returning to the Homeless Support System.

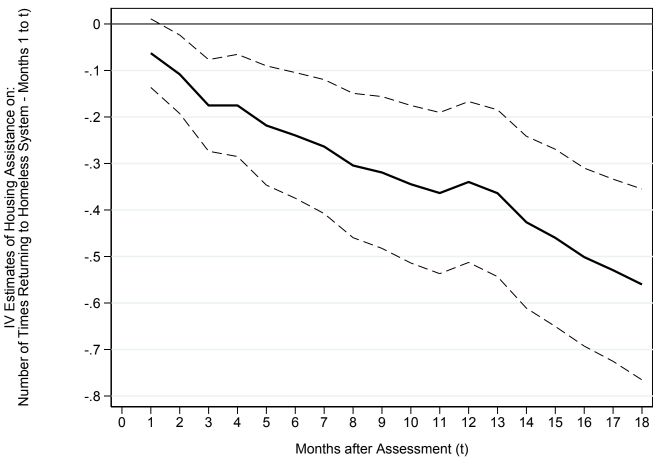
Note: Estimation sample consisting of 26,752 assessments processed in 2016-2017. Returns to the homeless support system include a new enrollment in a street outreach program or a new intake. Dashed lines show 90% confidence intervals.



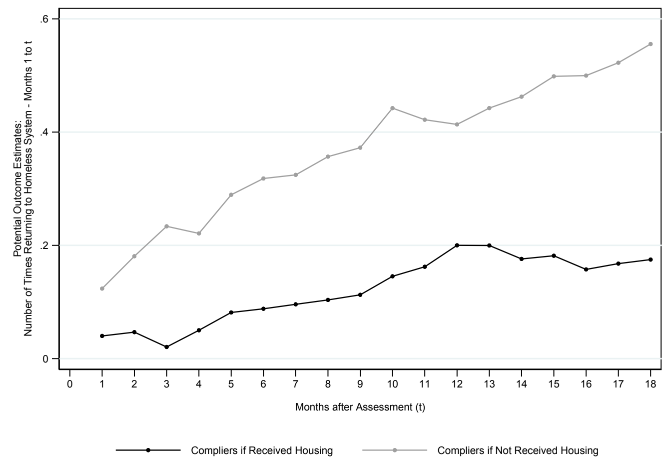
(a) IV Estimates: Pr(Receiving Housing Assistance - Month *t*)   **(b)** IV Estimates: Pr(Returned to Homeless Support System - Months *10* to *t*)

Figure 5. Post-Treatment Effect of Housing Assistance on Returning to Homeless Support System.

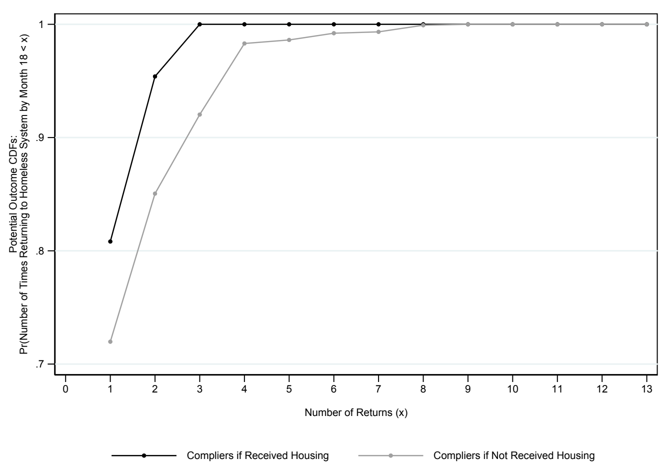
Note: Estimation sample consisting of 26,752 assessments processed in 2016-2017. In panel (a), any active enrollment in a housing program is considered. Grey bars show the share of individuals enrolled in a housing program in month *t* after intake. In panel (b), returns to the homeless support system include a new enrollment in a street outreach program or a new intake. Dashed lines show 90% confidence intervals.



(a) IV Estimates: No. of Returns to System – Months 1 to t



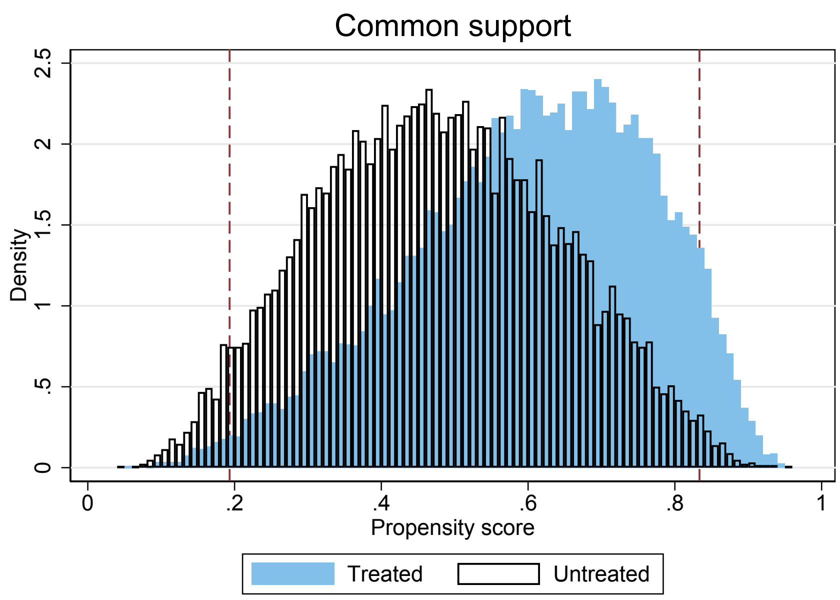
(b) Potential Outcomes: No. of Returns in Months 1 to t



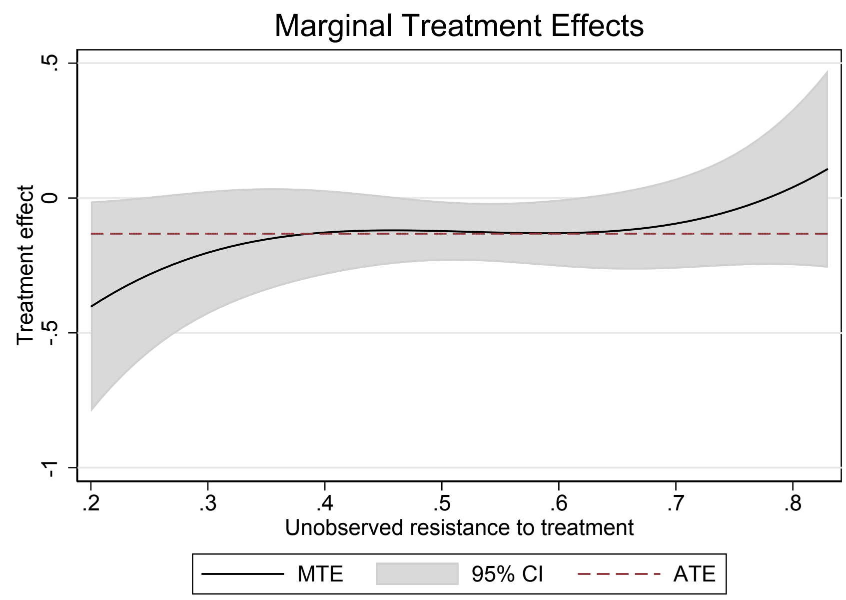
(c) Potential Outcome CDFs: No. of Returns by Month 18

Figure 6. The Effect of Housing Assistance on Number of Returns to the Homeless System.

Note: Estimation sample consisting of 26,752 assessments processed in 2016-2017. In Panel (a), returns to the homeless support system include a new enrollment in a street outreach program or a new acuity assessment. Dashed lines show 90% confidence intervals. In Panel (b), potential number of returns to the homeless support system for compliers if they receive housing assistance or not are plotted. In Panel (c), the potential number of returns to the homeless system by 18 months after intake for compliers in the case they receive housing assistance and in the case they do not are plotted.



(a) Common Support



(b) MTE Estimates: Pr(Returned to Homeless Support System - Months 1 to 18)

Figure 7. The Effect of Housing Assistance on Recidivism – Marginal Treatment Effects.

Note: Estimation sample consisting of 26,752 assessments processed in 2016-2017. The MTE estimates plotted are based on a local instrumental variables (IV) approach using a global cubic polynomial specification for the 1% trimmed sample with common support. Standard errors are based on 100 bootstrap replications.

10 Tables

Table 1. Testing for Random Assignment of Homeless Cases to Case Workers.

	Dependent Variables:				***Explanatory Variables:***	
	Pr(Received Housing Assistance)		**Case Worker Housing Placement Rate**		**Mean**	**Standard Deviation**
	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error		
Demographics:						
Age	0.000507*	(0.000273)	0.000	(0.000)	45.12	(11.23)
Female	0.0166**	(0.00654)	0.00246	(0.00212)	0.342	(0.474)
Black	0.142***	(0.0159)	0.00735*	(0.00401)	0.509	(0.500)
Hispanic	0.102***	(0.0161)	0.00638	(0.00417)	0.231	(0.421)
White	0.0949***	(0.0163)	0.00501	(0.00445)	0.195	(0.396)
Acuity Assessment:						
Acuity Score (0-17)	0.00116	(0.00149)	-0.00110	(0.000893)	7.267	(3.710)
Homeless History	-0.0275***	(0.00937)	-0.00212	(0.00262)	0.717	(0.450)
Chronic Homeless	-0.000266	(0.00968)	0.000	(0.00240)	0.613	(0.487)
Physical Disability	-0.00404	(0.00657)	0.00170	(0.00210)	0.697	(0.459)
Serious Mental Illness	-0.000262	(0.00789)	0.000480	(0.00251)	0.576	(0.494)
Self Care Problems	-0.0131	(0.00805)	-0.00603	(0.00440)	0.291	(0.454)
Used Crisis Service in Past 6 Months	-0.0170	(0.0162)	0.00421	(0.00481)	0.0425	(0.202)
Health, Criminal, Housing History (Past 12 Months):						
Any Department of Health Services (DHS) Treatment	0.0102	(0.00848)	0.00135	(0.00160)	0.172	(0.378)
Any Department of Mental Health (DMH) Treatment	-0.000210	(0.0103)	-0.000301	(0.00179)	0.116	(0.321)
Any Substance Abuse Treatment	-0.00106	(0.0108)	0.00322	(0.00206)	0.0846	(0.278)
Involvement with Law Enforcement Agencies	-0.0132	(0.00916)	-0.00106	(0.00188)	0.137	(0.343)
Received Emergency Cash Assistance	0.00306	(0.00864)	0.000453	(0.00176)	0.192	(0.394)
Any Interaction with Homeless System	0.0194	(0.0118)	0.000653	(0.00267)	0.351	(0.477)
Any Housing Assistance Recieved	0.0676***	(0.0148)	0.00433	(0.00336)	0.282	(0.450)
F-statistic for joint significance test	9.174		1.117			
p-value	0.000		0.329			
Number of Cases	26,752				26,752	

Note: Columns 1-4 show estimates for estimation sample of individuals assessed in 2016-2017. Columns 5-6 show descriptive statistics of cases in the estimation sample. All estimations include controls for site x month of assessment FEs. Reported F-statistic refers to a joint test of the null hypothesis for all variables. The omitted category for race is missing/multiple/other race. Standard errors are two-way clustered at the case worker and client level. *p<0.1, **p<0.05, ***p<0.01.

Table 2. First Stage Estimates of Housing Assistance on Case Worker Placement Rate.

	(1)	(2)	(3)	(4)
Controls:	Site X Month FEs	Add Demographics	Add Acuity Measures	Add History of Interaction with Public Agencies
Dependent Variable:	**Pr(Received Housing Assistance)**			
Case Worker Housing Placement Rate	0.661***	0.652***	0.652***	0.644***
	(0.0381)	(0.0380)	(0.0382)	(0.0377)
F-statistic (Instrument)	300.13	294.89	291.38	292.22
Dependent Mean	0.545	0.545	0.545	0.545
Number of Assessments	26,752	26,752	26,752	26,752

Note: Columns 1-4 show first stage estimates of different specifications on the estimation sample of assessments conducted in 2016-2017. Column 1 includes site x month of assessment fixed effects. Column 2 adds the individual demographics listed in Table 1. Column 3 adds acuity measures described in Table 1. Column 4 adds lagged outcomes variables described in Table 1. Standard errors are two-way clustered at the case worker and client level. *p<0.1, **p<0.05, ***p<0.01.

Table 3. Summary Statistics by Complier Type.

	Estimation Sample	Compliers (27%)	Always Takers (26%)	Never Takers (47%)
	(1)	(2)	(3)	(4)
Demographics:				
Age Above Median (47)	0.50	0.52	0.49	0.57
	(0.01)	(0.02)	(0.03)	(0.05)
Female	0.34	0.32	0.44	0.37
	(0.01)	(0.02)	(0.03)	(0.04)
Black	0.51	0.52	0.56	0.37
	(0.01)	(0.03)	(0.03)	(0.04)
Hispanic	0.23	0.19	0.18	0.26
	(0.01)	(0.03)	(0.03)	(0.04)
White	0.20	0.20	0.21	0.22
	(0.01)	(0.02)	(0.02)	(0.04)
Acuity Assessment:				
Homeless History	0.72	0.71	0.78	0.86
	(0.01)	(0.02)	(0.03)	(0.04)
Chronic Homeless	0.61	0.57	0.68	0.82
	(0.01)	(0.02)	(0.03)	(0.04)
Physical Disability	0.70	0.64	0.71	0.91
	(0.01)	(0.02)	(0.03)	(0.02)
Mental Disability	0.58	0.51	0.65	0.79
	(0.01)	(0.02)	(0.03)	(0.04)
Self Care Problems	0.29	0.20	0.32	0.34
	(0.01)	(0.03)	(0.04)	(0.04)
Past Health, Criminal, Housing History:				
Any DHS Treatment in Past 12 Months	0.17	0.17	0.14	0.14
	(0.003)	(0.02)	(0.02)	(0.03)
Any DMH Treatment in Past 12 Months	0.12	0.10	0.09	0.14
	(0.002)	(0.02)	(0.02)	(0.03)
Any Substance Abuse Treatment in Past 12 Months	0.08	0.08	0.09	0.07
	(0.002)	(0.02)	(0.02)	(0.02)
Involvement with Law Enforcement Agencies in Past 12 Months	0.14	0.13	0.14	0.18
	(0.002)	(0.02)	(0.02)	(0.04)
Received Emergency Cash Assistance in Past 12 Months	0.19	0.16	0.18	0.18
	(0.002)	(0.02)	(0.02)	(0.03)
Any Interaction with Homeless Support System in Past 12 Months	0.35	0.27	0.42	0.45
	(0.01)	(0.02)	(0.03)	(0.05)
Any Housing Assistance Recieved in Past 12 Months	0.28	0.23	0.34	0.27
	(0.01)	(0.02)	(0.03)	(0.04)

Note: The table shows summary statistics for compliers, always takers, and never takers of housing assistance within my estimation sample. Standard errors are computed using 100 clustered bootstrap replications.

Table 4. The Effect of Housing Assistance on Recidivism to Homelessness.

Dependent Variable:	**Pr(Ever Returned to Homeless System)**			**Number of Returns**
Time Period:	Months 1-9 after Assessment (1)	Months 10-18 after Assessment (2)	Months 1-18 after Assessment (3)	Months 1-18 after Assessment (4)
OLS: Housing Assistance	0.228***	0.0867***	0.243***	0.524***
No Controls	(0.0124)	(0.00902)	(0.0150)	(0.0322)
OLS: Housing Assistance	0.245***	0.106***	0.270***	0.563***
All Controls	(0.0120)	(0.00892)	(0.0130)	(0.0383)
OLS: Housing Assistance	0.248***	0.106***	0.274***	0.566***
Complier Re-weighted	(0.0122)	(0.00895)	(0.0132)	(0.0388)
RF: Housing Placement Rate	-0.108***	-0.131***	-0.133***	-0.361***
All Controls	(0.0325)	(0.0266)	(0.0336)	(0.0712)
2SLS: Housing Assistance	-0.168***	-0.204***	-0.206***	-0.560***
All Controls	(0.0543)	(0.0441)	(0.0564)	(0.125)
Dependent Mean	0.28	0.18	0.36	0.64
Complier Mean if No Housing Assistance	0.35	0.18	0.38	0.72
Number of Assessments	26,752	26,752	26,752	26,752

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table 5. IV Model with Three Treatment Options: 'Permanent Housing', 'Temporary Housing', and 'No Housing Treatment'.

	First Stages		Reduced Form		IV
	(1)	(2)	(3)		(4)
	Outcome: **Pr(Permanent Housing Placement)**	Outcome: **Pr(Temporary Housing Placement)**	Months 1-18 after Assessment **Pr(Returned to Homeless System)**		Months 1-18 after Assessment **Pr(Returned to Homeless System)**
A. Baseline Specification					
Instrument:				Outcome:	
Housing Placement Rate	0.644***		-0.133***	Housing Assistance	-0.206***
	(0.0377)		(0.0336)		(0.0564)
F-stat (Instrument)	292.22				
Dependent Mean	0.5449		0.3623		0.3623
B. Multiple Treatments Specification					
Instruments:				Outcomes:	
Permanent Housing Placement Rate	0.697***	-0.0338	-0.217***	Permanent Housing	-0.313***
	(0.0382)	(0.0313)	(0.0370)		(0.0547)
Temporary Housing Placement Rate	0.0119	0.605***	-0.0178	Temporary Housing	-0.0232
	(0.0244)	(0.0595)	(0.0380)		(0.0643)
SW F-stat (Instrument)	423.13	113.43			
Dependent Mean	0.1931	0.3518	0.3623		0.3623
Number of Assessments	26,752	26,752	26,752		26,752

Note: All specifications include service site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table 6. The Effect of Housing Assistance on Economic and Social Outcomes - Main Findings.

	Health		
Dependent Variable (1-18 Months after Assessment):	**Any Emergency Department Visit**	**Any Mental Health Treatment**	**Any Substance Abuse Treatment**
	(1)	(2)	(3)
OLS: Housing Assistance	0.00159	-0.00539	0.00753
All Controls	(0.00619)	(0.00380)	(0.0116)
RF: Housing Placement Rate	-0.0323*	-0.0292**	-0.0723
All Controls	(0.0178)	(0.0136)	(0.0473)
2SLS: Housing Assistance	-0.0541*	-0.0460**	-0.134
All Controls	(0.0302)	(0.0218)	(0.0878)
Dependent Mean	0.06	0.03	0.04
Number of Assessments	11,339	15,510	5,314
	Criminal Activity		
Dependent Variable (1-18 Months after Assessment:	**Jail Bookings**	**Number of Crimes**	**Any Probation**
OLS: Housing Assistance	0.217*	0.0332	0.00329
All Controls	(0.111)	(0.0348)	(0.00362)
RF: Housing Placement Rate	-0.955**	-0.247**	-0.0230
All Controls	(0.389)	(0.115)	(0.0166)
2SLS: Housing Assistance	-1.507**	-0.389**	-0.0363
All Controls	(0.621)	(0.182)	(0.0261)
Dependent Mean	1.05	0.31	0.033
Number of Assessments	15,510	15,510	15,510
	Employment and Income (Any Report)		
Dependent Variable (1-18 Months after Assessment):	**Any Income**	**Employed**	**Social Benefits**
OLS: Housing Assistance	0.146***	0.0834***	0.130***
All Controls	(0.0109)	(0.00794)	(0.0107)
RF: Housing Placement Rate	0.162***	0.152***	0.0566
All Controls	(0.0366)	(0.0447)	(0.0397)
2SLS: Housing Assistance	0.264***	0.242***	0.0923
All Controls	(0.0609)	(0.0724)	(0.0646)
Dependent Mean	0.76	0.14	0.67
Number of Assessments	23,054	23,387	23,054

Note: All specifications include service site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table 7. The Costs and Benefits of Housing Assistance for the Homeless.

	Costs	Benefits (Savings) of Public Agencies Expenditures				
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable (Months 1-18 After Assessment):	Days Spent in Housing Programs	Overall	Future Returns to Homelessness	Health	Law Enforcement	Employment
A. Housing Assistance - All Types						
IV: Housing Assistance	10,366***	-8,044***	-2,102***	-2,796*	-1,724***	-1,146***
	(1,020)	(1,713)	(469.5)	(1,583)	(549.6)	(388.2)
Dependent mean	3,752	5,723	2,413	1,264	941	-138
Number of Assessments	26,752	10,305	26,752	11,339	15,510	23,054
B. Housing Assistance - By Type						
IV: Permanent Housing Assistance	12,402***	-8,053***	-2,885***	-2,085	-1,746***	-1,862***
	(831.6)	(1,642)	(420.6)	(1,753)	(552.9)	(340.0)
IV: Temporary Housing Assistance	5,095***	-4,757**	-557.6	-3,214*	-1,089*	353.7
	(654.7)	(2,048)	(452.4)	(1,742)	(573.5)	(250.9)
Dependent mean	3,752	5,723	2,413	1,263	941	-138
Number of Assessments	26,752	10,305	26,752	11,339	15,510	23,054

Note: Estimation sample and specification with all controls. Standard errors are two-way clustered at the case worker and individual level. Direct housing costs are set to $35 per day for temporary housing, $40 per day for rapid rehousing, and $50 per day for permanent supportive housing, according to the 2017 Los Angeles Housing Gap Analysis. Future returns costs are estimated based on an average housing cost of $4,000 per return, based on direct housing costs computed in column (1). Health costs are the sum of DHS and DMH costs. Law enforcement costs are the costs of jail days and probation months. Cost estimates are taken as described in the text. Net transfers are computed as the total cash transfers, computed as the difference between total income and wage, and taxes received are set at 15% of wages. Overall costs are the sum of columns 3-6. All costs and benefits are estimated for an 18-month period. *p<0.1, **p<0.05, ***p<0.01.

A Additional Background

A.1 Homelessness in Los Angeles County: Overview

Los Angeles County's homeless population is the second largest in the United States. Although the composition of its homeless population is quite different compared to other communities in the country, the characteristics of its single adult homeless population, as well as the federal funding levels per homeless person counted, are similar to those in many other communities.

Figure A.1 graphs Los Angeles Continuum of Care's (CoC) homeless rate over time.[38] Panel (a) includes both unsheltered and sheltered homeless individuals, while panel (b) includes only unsheltered homeless individuals.[39] In 2010, there were an estimated 360 homeless individuals per 100,000 in Los Angeles CoC. This rate has increased by 70 percent over time, with a rate of 608 per 100,000 in 2019, with 460 of them unsheltered. In 2019, Los Angeles CoC had the nation's second largest homeless population (approximately 60,000 individuals) and the largest unsheltered homeless population. The figure also plots the time trend in homeless rates for the New York City CoC and the rest of the country. For comparison, New York City CoC, which has the largest homeless population in the nation, has also experienced a similar increase over this period, although its increase was driven by sheltered homeless, since it has a right-to-shelter policy. In contrast, when considering the rest of the U.S., the homeless rate has declined by 21 percent, from 184 per 100,000 in 2010 to 144 per 100,000 in 2019.[40]

Comparing Los Angeles County and New York City to the rest of the CoCs shows that despite their extraordinary large homeless populations, they share some similarities with other communities in the U.S., as can be seen in Figure A.2, which plots homeless rates versus designated homeless beds (in both temporary and permanent housing programs) for 371 CoCs in 2019. The dashed line in the figure presents the fitted line from a linear regression of beds rate on homeless rate. The fitted line has a positive slope, implying that CoCs with a higher rate of beds per capita have a higher homeless rate. In particular, there are several CoCs with a similar homeless and beds rates to that of Los Angeles CoC.

[38] Continuum of Cares (CoCs) are geographic units at which providers of homelessness assistance jointly apply for federal resources and develop a strategic plan to address homelessness within their jurisdiction. CoCs vary in size and composition and can be comprised of single cities, individual counties, several counties, or entire states. In 2019, there were 394 CoCs in the United States and its territories.

[39] An unsheltered homeless is defined as an individual spending the night in a place not meant for human habitation (e.g., street). A sheltered homeless is defined as an individual spending the night in a temporary housing program (e.g., emergency shelter).

[40] Evans et al. (2019) and O'Flaherty (2019) show that the large increases in homeless rates in Los Angeles CoC and New York City CoC cannot be explained by the rising housing prices in these CoCs alone, and call for additional research trying to find additional determinants of homelessness in these CoCs, which together comprise 25% of the entire homeless population in the U.S.

The homeless population in Los Angeles CoC is somewhat different compared to that in the rest of the U.S. along some dimensions. Columns 1-2 of Table A.1 present the characteristics of the homeless populations of Los Angeles CoC and the rest of the United States, as of 2019, respectively. The first important difference between Los Angeles and the rest of the U.S. is that only 25% of Los Angeles' homeless population is sheltered, compared to 68% of the homeless population in the rest of the country. It is not clear why the unsheltered homeless population in Los Angeles CoC is so large, but several explanations include high housing prices, lack of designated homeless housing, zoning laws and NIMBYism, and the moderate climate (See Byrne et al., 2013; Cohen, 2019; Corinth, 2017; Corinth and Lucas, 2018). Additionally, homeless individuals in Los Angeles CoC are less likely to be female (31% compared to 40% in the rest of the U.S.), more likely to be part of a minority group (10% consider themselves non-Hispanic whites compared to 28% in the rest of the country), less likely to be part of a family (15% of individuals compared to 32% in the rest of the country), more likely to be chronically homeless (28% compared to 18% in the rest of the country), and more likely to suffer from severe mental illness (27% compared to 20% in the rest of the country).[41]

Columns 3-4 of Table A.1 compare the characteristics of single individuals experiencing homelessness in Los Angeles CoC and the rest of the country, respectively. This is more relevant for my study since it focuses on the single adult homeless population.[42] Even when restricting attention to single individuals, a lot fewer are sheltered in Los Angeles CoC (15%) compared to the rest of the country (56%). However, Los Angeles CoC's single individuals experiencing homelessness share some similarities with single individuals experiencing homelessness in the rest of the country. For example, approximately 70% are male, blacks are over-represented (40% in Los Angeles CoC and 34% in the rest of the US), and the share of chronically homeless is larger compared to the general homeless population (31% in Los Angeles CoC and 23% in the rest of the country).

Homeless programs and services have three main sources of funding: federal, local, and private. Federal funding supports homeless programs through multiple agencies, the largest the Department of Housing and Urban Development (HUD), which provides approximately 40% of overall federal funding (USICH, 2020). In addition, local governments (states, counties and cities) provide their own funding. Unfortunately, consistent data on local and private funding does not exit at the CoC level and one must rely on federal funding data to make

[41] Chronically homeless individual refers to an individual with a disability who has been continuously homeless for one year or more or has experienced at least four episodes of homelessness in the last three years, with a combined time homeless of at least 12 months (Henry et al., 2018).

[42] To be precise, my definition of single adult excludes individuals under 25 or above 65, while the single individuals category does not.

comparisons across CoCs. The largest of the federal grants is the Continuum of Care (CoC) Program Grant, which distributes more than \$2 billion dollars for homeless programs annually.[43] In 2018, the average CoC received \$5.6 million dollars in CoC grants, or \$5,000 dollars per homeless person counted. Los Angeles CoC received slightly more than \$123 million dollars, the second largest grant after New York City, but this was translated to only \$2,476 per homeless person counted.

The significant increase in the homeless population and the low federal spending rates per homeless person counted in LA County have led decision makers, backed up by the public, to allocate more resources to address the problem of homelessness.[44] As a result, for example, the county's overall budget for homelessness in 2018 was \$619 million (LA Times, 2018), with only \$130 million (approximately 20 percent) granted by HUD, implying that LA County spent on average \$11,000 per homeless person counted in 2018.

A.2 Housing Assistance for the Homeless in Los Angeles County: Background

In this section, I briefly describe the different types of housing assistance programs available to individuals experiencing homelessness in Los Angeles County. Housing assistance programs in Los Ageles CoC generally follow the Housing First strategy for addressing homelessness, which is based on quickly finding housing solutions (preferably permanent) for individuals experiencing homelessness, in order to minimize the trauma caused by homelessness and to better serve additional problems an individual experiencing homelessness is facing (Burt et al., 2017).

The housing programs that serve the homeless population in Los Angeles County can be broadly categorized into two types: Temporary and Permanent. Temporary housing programs, as the name suggests, provide housing assistance for a short period of time and are meant to provide crisis housing until the person is able to find a permanent housing solution. These programs are composed of two sub-types: Emergency Shelter and Transitional Housing. Permanent housing programs provide housing assistance for a medium or long-term period and are based on finding a permanent housing solution for the client, which could be used

[43] See Appendix A for a more detailed information on federal funding for homelessness and on local funding for Los Angeles County.

[44] County voters have supported increasing homeless spending by approving billions of dollars in bonds that would provide tens of thousands of affordable housing units and services for the homeless. Some of the important propositions and measures are worth mentioning. In 2016, more than 77 percent of L.A. City voters supported Proposition HHH, a \$1.2 billion housing bond, to fund 10,000 units of supportive housing over the next decade. Then, in March of 2017, 69 percent of L.A. County voters approved Measure H, a \$3.5 billion tax-funded measure for homeless services and rental subsidies that would provide permanent housing for 45,000 families and individuals, while preventing homelessness for 30,000 others. In addition, other affordable housing measures were approved by city, county, and state voters, including Measure JJJ in 2016, State Propositions 1 and 2 in 2018, and L.A. City's linkage fee on housing developers in 2017.

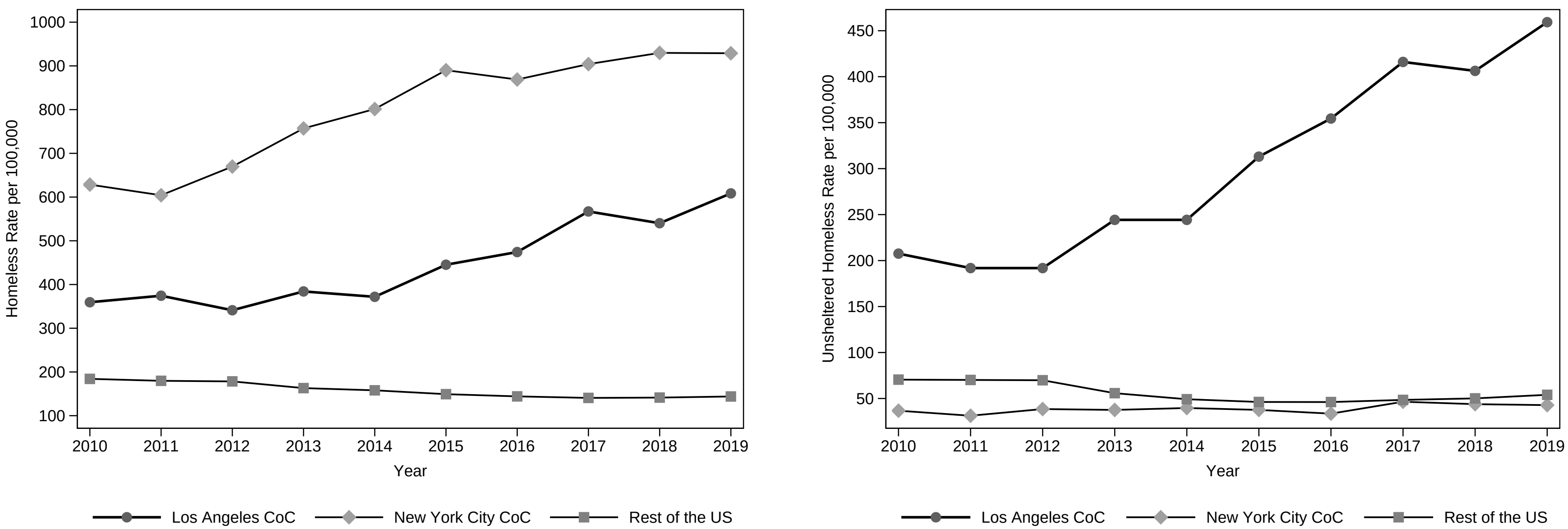
even after housing subsidy has ended. The three main permanent housing programs are Rapid Re-Housing, Permanent Supportive Housing, and Other Permanent Housing.

In Los Angeles CoC, as of 2019, there was a total of 45,116 beds in 764 housing assistance programs that serve the homeless or previously homeless population (LAHSA, 2019). 25,608 (57%) beds in 630 programs serve the single adult homeless population, and the rest serve families or children and youth experiencing homelessness. When considering the distribution of beds serving the single adult population, 7,184 beds (28% of all single adult beds) are in temporary housing programs and 18,424 (72% of all single adult beds) are in permanent housing programs. The average housing assistance program has 40 beds (an average of 49 for temporary housing programs and an average of 27 for permanent housing programs). The largest temporary housing program is the Los Angeles Mission Overnight Beds for Men with 212 beds, and the largest permanent housing program is Step Up on Second's DHS Scattered Sites permanent supportive housing program with 343 beds.

The Housing First policy, combined with the low supply of beds available to serve the single adult homeless population, has two implications. First, there is a long waiting list for any type of housing assistance. The shortest is for temporary (70 days on average in my data), and the longest is for permanent (150 days on average in my data). Second, individuals with a higher level of needs or more acute situations (e.g., severe mental illness, substance abuse problems, chronic homelessness) are being prioritized into housing assistance, especially for permanent housing programs, implying that there is selection into housing assistance based on observables. This is one motivation for me to find a source of exogenous variation in housing assistance receipt using an instrumental variable research design.

Finally, it is important to note that many housing assistance programs offer non-housing services as well to support the rehabilitation process of participants, especially in permanent housing programs. In addition, the homeless support system offers additional non-housing assistance programs.[45] The most common non-housing services include case management, basic hygiene services (e.g., meals and showers, health care), substance abuse treatment, mental health treatment, life skills courses, and employment readiness courses.

[45] In my data, 35% of housing assistance programs participants were also enrolled in at least one non-housing assistance program while receiving housing assistance.



(a) Overall Homeless Rate

(b) Unsheltered Homeless Rate

Figure A.1. Homeless Trends in Los Angeles CoC, New York City CoC, and the Rest of the U.S.

Note:: Los Angeles CoC (Continuum of Care) includes all of Los Angeles County, excluding the cities of Glendale, Long Beach, and Pasadena. NYC CoC refers to the New York City continuum of care, and the rest of the US includes 372 CoCs that have available data from 2010-2019. CoC population is defined as the average estimates from the 2013-2017 ACS. The 374 CoCs included in this analysis cover 97.5% of the U.S. population. Panel (a) includes unsheltered homeless individuals and individuals receiving temporary housing assistance. Panel (b) includes only unsheltered homeless individuals.

Source: Byrne et al. (2013), US Department of Housing and Urban Development (HUD) Point-in-Time (PIT).

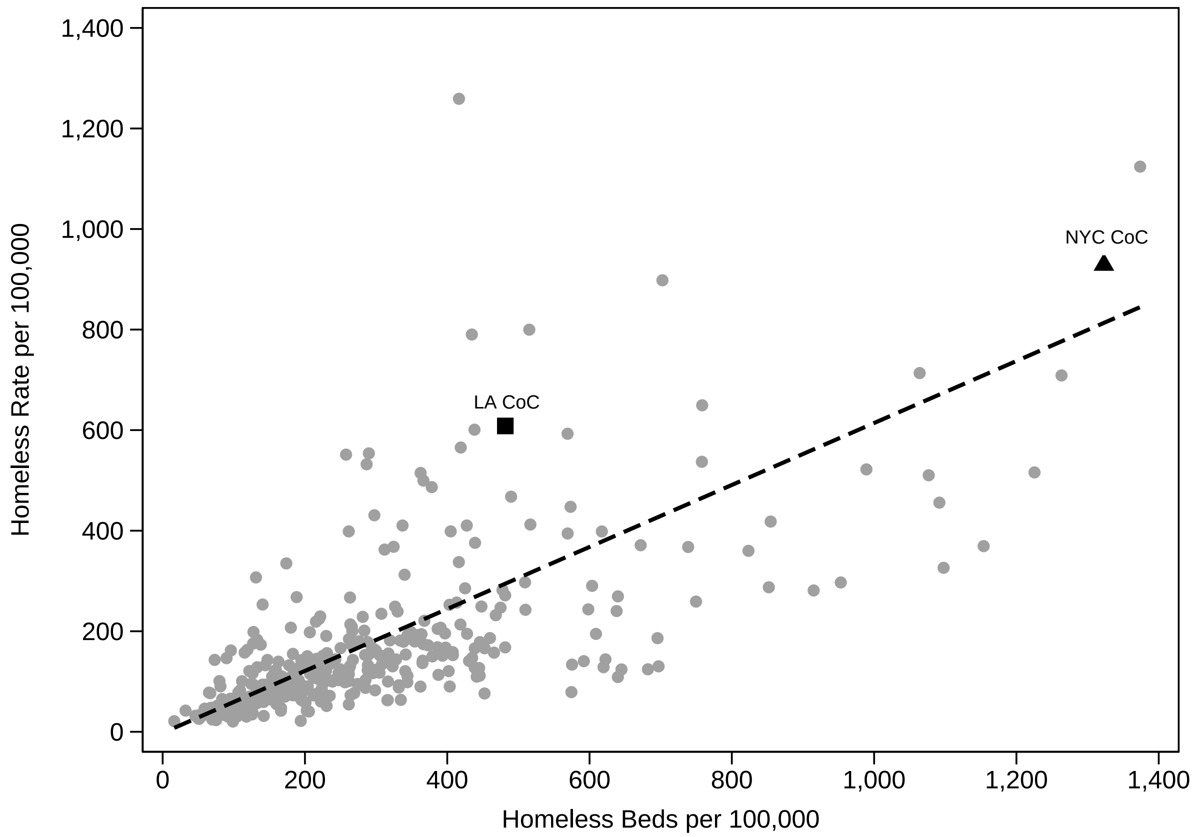


Figure A.2. Homeless Rates versus Homeless Beds Per Capita, 2019.

Note: Sample consists of 371 CoCs with available data on homeless counts and designated homeless beds counts (both temporary and permanent housing programs included). The dashed line presents the linear fit between homeless rate and beds rate, with a 0.5 coefficient and .028 standard error. 3 CoCs with a homeless beds rate per 100,000 larger than 1,500 are excluded from the figure.

Source: Byrne et al. (2013), US Department of Housing and Urban Development (HUD) Point-in-Time (PIT).

Table A.1. Characteristics of Individuals Experiencing Homelessness, 2019.

	Overall Population		Single Individuals	
	Los Angeles CoC	Rest of US	Los Angeles CoC	Rest of US
	(1)	(2)	(3)	(4)
Overall Homeless Population	56,257	505,927	47,810	344,899
Homeless Rate (per 100,000)	608	164	517	112
Shelter Type:				
Sheltered	0.25	0.68	0.15	0.56
Unsheltered	0.75	0.32	0.85	0.44
Gender:				
Females	0.31	0.40	0.26	0.30
Males	0.67	0.60	0.71	0.69
Race/Ethnicity:				
Black	0.43	0.40	0.40	0.34
Hispanic	0.36	0.20	0.36	0.16
White	0.10	0.28	0.21	0.47
Other Race/Ethnicity	0.11	0.12	0.03	0.03
Household Type:				
Families	0.15	0.32	-	-
Anyone Else	0.85	0.68	-	-
By Age:				
Under 18 Years Old	0.09	0.20	0.001	0.01
18-24 Years Old	0.06	0.08	0.06	0.09
> 24 Years Old	0.85	0.72	0.93	0.90
Special Populations (18+ Years Old):				
Chronically Homeless	0.28	0.18	0.31	0.23
Veterans	0.06	0.07	0.07	0.10
Severely Mentally Ill*	0.27	0.20	-	-
Chronic Substance Abuse*	0.16	0.16	-	-
HIV Positive*	0.02	0.07	-	-

Note: Column 1-4 show different demographic characteristics of individuals experiencing homelessness. Columns 1-2 consider the overall homeless population, while columns 3-4 consider the single individuals homeless population. Columns 1 and 3 show demographics for Los Angeles CoC, while columns 3 and 4 show demographics for the rest of the US.

Source: United States Department of Housing and Urban Development (HUD) 2019 Point-in-Time (PIT) Report, Los Angeles Homeless Services Authority (LAHSA) Point-in-Time Report, Byrne et al. (2013).

Table A.2. Treatments Received.

	Number of Cases	Percent of Cases
	(1)	(2)
1. Permanent Supportive Housing (PSH):	1,962	100%
Permanent Supportive Housing (PSH) Only	564	29%
with Non-Housing Services (NH)	370	19%
with Temporary Housing (TH)	370	19%
with Temporary Housing (TH) and Non-Housing Services (NH)	429	22%
with Rapid Re-Housing (RRH)	76	4%
with Rapid Re-Housing (RRH) and Temporary Housing (TH)	38	2%
with Rapid Re-Housing (RRH) and Non-Housing Services (NH)	56	3%
with Rapid Re-Housing (RRH), Temporary Housing (TH), and Non-Housing Services (NH)	59	3%
2. Rapid Re-Housing (RRH):	3,204	100%
Rapid Re-Housing (RRH) Only	1,522	48%
with Temporary Housing (TH)	554	17%
with Non-Housing Services (NH)	567	18%
with Temporary Housing (TH) and Non-Housing Services (NH)	561	18%
3. Temporary Housing (TH):	9,412	100%
Temporary Housing (TH) Only	6,321	67%
with Non-Housing Services (NH)	3,091	33%
4. Non-Housing Services (NH):	4,031	100%
5. No Treatment Received	8,143	100%

Note: The initial sample consists of all assessments processed in Los Angeles County's Coordinated Entry System in 2016-2017.

B Data Description and Construction

B.1 Data Sources

My analysis relies on data from several administrative sources. Table B.1 lists each administrative source, files provided, and the time period covered by the associated files.

Table B.1. List of Data Sources.

Source	Data	Time Period
Los Angeles Continuum of Care (CoC) Homeless Support System	(1) Homeless Single Adults Intakes (VI-SPDAT)	
	- Demographics (age, race, gender, veteran status)	01/2016-12/2018
	- Acuity indicators (homeless history, disabilities)	
	- Location of intake (SPA)	
	- Intake Date	
	- Case worker name	01/2016-02/2018
	- Agency name	
	(2) Homeless Management Information System (HMIS)	01/2010-06/2019
	- Homeless programs placements (housing and non-housing)	
	- Program start date and end date (when relevant)	
	- Program information (agency, name, type)	
	- Intake and exit interviews (demographics, health, employment and income, social benefits receipt, destination)	
Enterprise Linakge Project (ELP)	(3) Los Angeles County Department of Health Services (DHS)	01/2006-05/2018
	- Services received by DHS	
	- Facility, claim amount, type of service, start/end date	
	(4) Los Angeles County Department of Mental Health (DMH)	01/2006-08/2018
	- Services received by DMH	
	- Facility, claim amount, type of service, start/end date	
	(5) Los Angeles County Department of Public Health (DPH)	01/2006-12/2017
	- Services received by DPH (substance abuse treatments)	
	- Facility, claim amount, type of service, start/end date	
	(6) Los Angeles County Department of Public and Social Services (DPSS)	02/2010-08/2018
	- General Relief (GR) amount paid monthly	
	- Homelessness Indicator	
	(7) Los Angeles County Sheriff Department (LASD)	04/2005-08/2018
	- Criminal charges	
	- Arrests	
	- Incarceration history	
	(8) Los Angeles County Department of Probation	01/2005-08/2018
	- Start and end date of probation service	

Note: This table lists data sources, files, and the time period covered by the associated files.

B.2 Description of Files

Vulnerability Index - Service Prioritization Decision Assistance Tool (VISPDAT). Information on the initial interaction between a client and a case worker comes from the Vulnerability

Index - Service Prioritization Decision Assistance Tool (VI-SPDAT) assessments data, which correspond to a survey conducted to single adults seeking assistance from the county's homeless support system. The dataset contains information for all assessments over the period 2016-2018. The VI-SPDAT survey is a pre-screening tool that guides case workers to determine the level of acuity of a particular client, which in the case of single adults ranges from a score of 0 to 17. Higher levels of the VI-SPDAT score indicate a higher level of acuity and, hence, a higher need for assistance. In addition, the VI-SPDAT contains a client's unique identifier assigned by the system, the date of the assessment, the acuity score, demographic characteristics of the clients such as age, race, gender, disabilities and veteran status. It also contains each of the questions that determine the acuity score. Finally, it contains the names of the case workers assigned to conduct the assessments, the organization where they conduct the survey and the location of the organization.

Homeless Management Information System (HMIS). The Homeless Management Information System (HMIS) contains complete records of all homeless services provided by service providers in Los Angeles County's homeless response system. The HMIS is a local information technology system used to collect client-level data and data on the provision of housing and services to homeless individuals and families and persons at risk of homelessness. I have access to this data for the Los Angeles Continuum of Care from 2010 through June 2019. The HMIS reports information for all people considered homeless, that is families, single adults and youth, and each observation corresponds to an individual who can be tracked in time using a unique individual identifier. For each person in the HMIS, I observe demographic characteristics such as age, gender, disabilities, veteran status, chronic homeless status and type of service and/or housing program (street outreach, shelter, temporary housing, long-term housing, and non-housing services). For each program I observe the enrollment date, the exit date when the service has finished, and the amount of the subsidy if it corresponds. For a subsample of the population in the HMIS I observe reported information on income, employment, social benefits receipt, as well as health status.

Los Angeles County Department of Health Services (DHS) Service Records. The Los Angeles County Department of Health Services (DHS) is the second largest municipal health system in the nation. DHS's mission is to ensure access to high-quality, patient-centered, cost-effective health care to Los Angeles County residents. DHS is as an integrated health system, operating 26 health centers and four acute care hospitals, in addition to providing health care to youth in the juvenile justice system and inmates in the LA County jails. Moreover, DHS runs the County's 911 emergency response system. Across the network of DHS's directly operated clinical sites and through partnerships with community-based clinics, DHS cares for about 750,000 unique patients each year, employs over 22,000 staff, and has an annual operating budget of $6.2 billion.[46]

The DHS service records contain information on facility, type of service (inpatient, outpatient, emergency department), payee, and start and end dates of services. Additionally, the records contain diagnosis and procedure codes.

Los Angeles County Department of Mental Health (DMH) Service Records. The Los Angeles County Department of Mental Health is the largest county-operated mental health department in the United States, directly operating programs at more than 85 sites, and further providing services through contract programs and DMH staff at approximately 300 sites co-located with other County departments, schools, courts and various organizations. Each year, the County contracts with close to 1,000 organizations and individual practitioners to provide a variety of mental health-related services. On average, more than 250,000 County residents of all ages are served every year. Its mission is to enhance the well-being of LA's most vulnerable populations (such as the homeless).

The DMH service records contain information on mental health services provided, including assessments, case management, crisis intervention, medication support, peer support, psychotherapy and other rehabilitative services. In addition, they include information on the facility, claim amount, and start and end date of services.

Los Angeles County Department of Public Health (DPH) Service Records. The Los Angeles County Department of Public Health's mission is to protect health, prevent disease, and promote health and well-being for everyone in Los Angeles County. DPH educates the population on good health practices, advocates for access to medical health coverage, ensures safe drinking water, promotes childhood vaccination, and provides sex education. It also provides clinical services through 14 public health centers (plus a satellite site on Skid Row).

The DPH service records contain information on substance-abuse related services, including detox, residential programs, and outpatient visits, among others. It contains information on the facility, payment method, type of service, and start and end date of services. Additionally, it includes an intake questionnaire containing 92 questions regarding various topics, from addiction history and medical history, to employment status.

General Relief (GR) Records. General Relief is an emergency cash assistance program operated through the Department of Public and Social Services (DPSS), the department

[46] https://dhs.lacounty.gov/more-dhs/about-us/

responsible for providing social service benefits in Los Angeles County. DPSS provides services like Cash Assistance (CalWorks), Food and Nutrition (CalFresh), Health Assistance, Job Assistance (GROW), General Relief (GR), and other community services. DPSS serves 10 million residents with an annual budget of $3.9 Billion. The General Relief records contain the monthly benefits each member of a household receives, as well as two indicator variables that can be used to identify homeless recipient. General Relief is distributed via EBT card. Eligible for General Relief are those individuals who are unable to work and are not eligible for other state or federal cash assistance programs. GR includes a monthly grant of $221 for a single person.

Los Angeles County Sheriff's Department (LASD) Records. The Los Angeles Sheriff's Department (LASD) provides general law enforcement services to 40 contract cities; 90 unincorporated communities; 216 facilities, hospitals, and clinics located throughout the County; nine (9) community colleges; the Metropolitan Transit Authority; and 47 Superior Courts. LASD also provides services such as laboratories and academy training to smaller law enforcement agencies within the County. Additionally, LASD is responsible for securing approximately 18,000 inmates daily in 7 custody facilities, which includes providing food and medical treatment.[47]

The LASD records contain information on the population of charged and incaracerated individuals in Los Angeles County (2005-2018). The dates of each unique sentence are observed, as well as the type of charge and the total sentence length. Specifically, the data contain records of criminal charges, arrests (jail bookings), and incarceration history. For criminal charges, date and type of crime committed are specified.

Los Angeles County Probation Department Records. The Probation Department is responsible for enhancing public safety, ensuring victim's rights, and effecting positive probationer behavioral change. The Probation Department provides several adult services like supervision after release, investigations, AB 109, and specialized treatments for moderate-to-high-risk clients. In addition, they provide juvenile services such as diversion and prevention, supervision and school based programs. They operate on a $935 million budget and in 50 different facilities, working with 82,000 adults and 1000 juveniles.

The probation records contain information on whether an individual is under probation in a given month and the facility at which they are serving the probation period.

[47]The Sheriff's data will not contain data for Los Angeles city jails except for those arrestees who remain in custody after arraignment. These individuals are remanded to the custody of the LA County Sheriff's department.

B.3 Data Cleaning and Sample Construction

The following provides detailed steps of the cleaning and restrictions I impose on different data sources used in the study.

B.3.1 Vulnerability Index - Service Prioritization Decision Assistance Tool (VISPDAT). Steps involved in creating and cleaning the data:

1. Combine four different versions of the VI-SPDAT intake data that were given to me at different points in time, each version containing all previous intakes in addition to new intakes.
   (a) Label all variables and variable values, drop observations with serious data entry mistakes (no personal ID, missing values in all fields, etc.).
   (b) Standardize variable types and names across all four versions.
2. Combine four data versions into one version.
   (a) Keep record from most recent version in case of duplicates.
   (b) Combined data sets contain 87,500 records of new intakes.
3. Drop duplicate intakes.
4. Keep assessments conducted in 2016-2017.
5. Keep assessments conducted for individuals age 25-65.
6. Clean agency and case worker names and assign identifiers.
   (a) Agency and case worker names available for intakes from 01/2016 through 02/2018.
   (b) Manually standardize names: convert strings to uppercases, remove special characters, fix spelling mistakes, change acronyms to full provider names, change nicknames to full names.
   (c) Assign agency identifier and worker-agency identifier (do not allow for case workers to work on multiple agencies).
   (d) Link clean agency and case-worker identifiers to main intake data.
   (e) Overall, there are 350 sites (defined as agency-area combination) and 3,028 unique case workers.
7. Drop cases with missing case worker, agency, or site information.

8. Remove duplicates or multiple-day intakes.

9. Remove veteran cases since their assignment does not affect case worker housing placement rate (they are automatically referred to the VA homeless system).

10. Keep case workers with more than 15 non-veteran cases handled in 2016-2017. I impose this restriction to avoid concerns regarding small cell sizes.

11. Keep sites with at least 2 case workers conducting intakes in a given month. This is done in order to keep only cases that were as-good-as-randomly assigned to case workers.

B.3.2 Homeless Management Information System (HMIS). The HMIS consists of 12 different files, each recording different items: Client, Disabilities, Employment and Education, Enrollment, Exit, Funder, Health and Domestic Violence, Income and Benefits, Inventory, Project, Services, and Site. The steps involved in creating and cleaning the combined HMIS data:

1. Combine four different versions of each file in the HMIS that were given to me at different points in time, each version containing all previous intakes in addition to new intakes.
    (a) Label all variables and variable values, drop observations with serious data entry mistakes (no personal ID, missing values in all fields, etc.).
    (b) Standardize variable types and names across all four versions.

2. Combine four data versions into one version and merge all files into one "master" HMIS data based on enrollment identifier which links all data files.
    (a) Keep record from most recent version in case of duplicates.

3. Keep records only for individuals in the intake data (both intake and HMIS data use similar personal identifiers).

4. For programs with missing date, compute end date based on the following algorithm:
    (a) If last service date is found, assign it to be exit date.
    (b) Assign median program length in cases with no exit date or last service date that time from enrollment surpassed maximum length of stay for program (for example, 3 months for emergency shelter).

(c) Assign last date of data (06/31/2019) to programs with no exit date or last service date, where the time passed from enrollment date is lower than maximum duration of the program.

5. Construct a panel dataset at the case-monthly data.

The key variables from the HMIS data are:

1. Housing assistance receipt: enrollment (yes/no), number of program enrollments, number of housing assistance days. This is done for housing assistance in general, and separately for temporary and permanent housing assistance programs.

2. Recidivism to homeless system: defined as new intake (Intakes data) or a new enrollment in a street outreach program (these are programs that serve individuals who live on the streets, implying the individual is homeless again).

3. Destination: individuals report the destination to which they are headed to at program exit (any program type). Destinations include permanent, temporary, or no housing solutions.

4. Benefits, employment, and income: Individuals report whether they receive social benefits, whether they are employed, and what their monthly income is.

B.3.3 Enterprise Linkage Project (ELP). The linkage process of records between the various administrative sources and the HMIS records is a complex process. Each month, the individual county agencies run an encryption code that scrambles the names, birthdates, and social security numbers of the individuals in their data. The de-identified data is then uploaded to a secure server for inclusion into the ELP. Staff in the Research and Evaluation Services division of the Service Integration branch then run a matching code that uses the encrypted identifiers to link people together across agencies. The linkage process uses a combination of perfect and fuzzy matches based on combinations of SSN, and date of birth (Hess and Carollo, 2017).

The following steps were done in cleaning and constructing the various outcomes for the different ELP data sources:

1. Label all variables and variable values, drop observations with serious data entry mistakes (no personal ID, missing values in all fields, etc.).

2. Keep records only for individuals in the intake data (both intake and HMIS data use similar personal identifiers).

3. Remove duplicate records.

4. Construct a panel dataset of the case-monthly data, collapsing services for each agency.

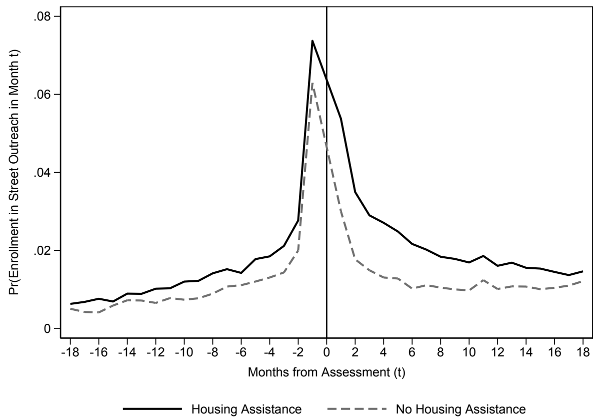
5. Merge all monthly panel data for each agency into one large panel dataset.

The key variables from the ELP data are:

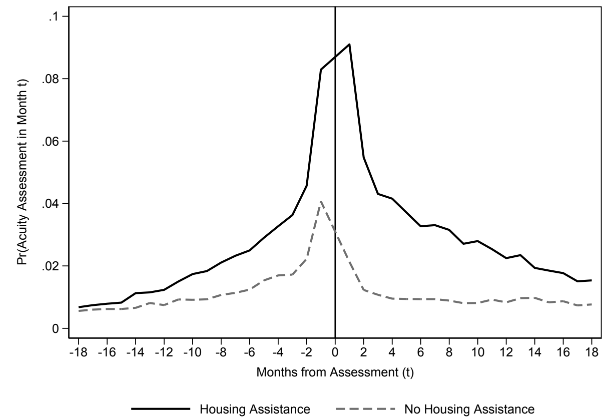
1. Health (DHS, DMH, DPH): any service received (yes/no), number of services received, duration of services received.

2. Crime: Criminal charges, jail bookings (arrests), jail days, probation days.

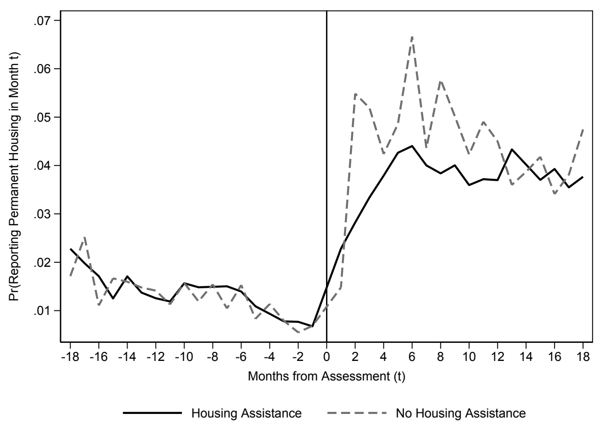
3. Social Benefits: General relief receipt.



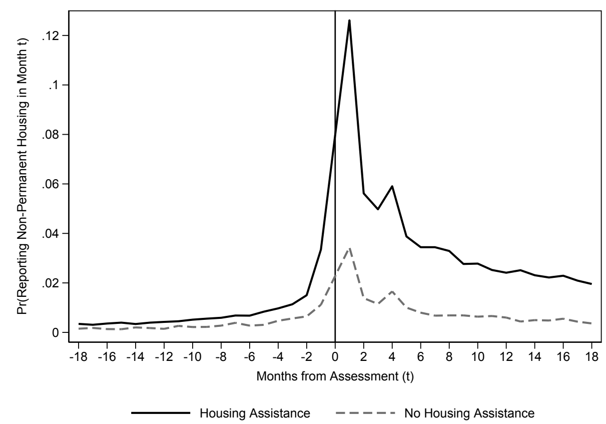
(a) Enrollment in a Street Outreach Program



(b) New Acuity Assessment



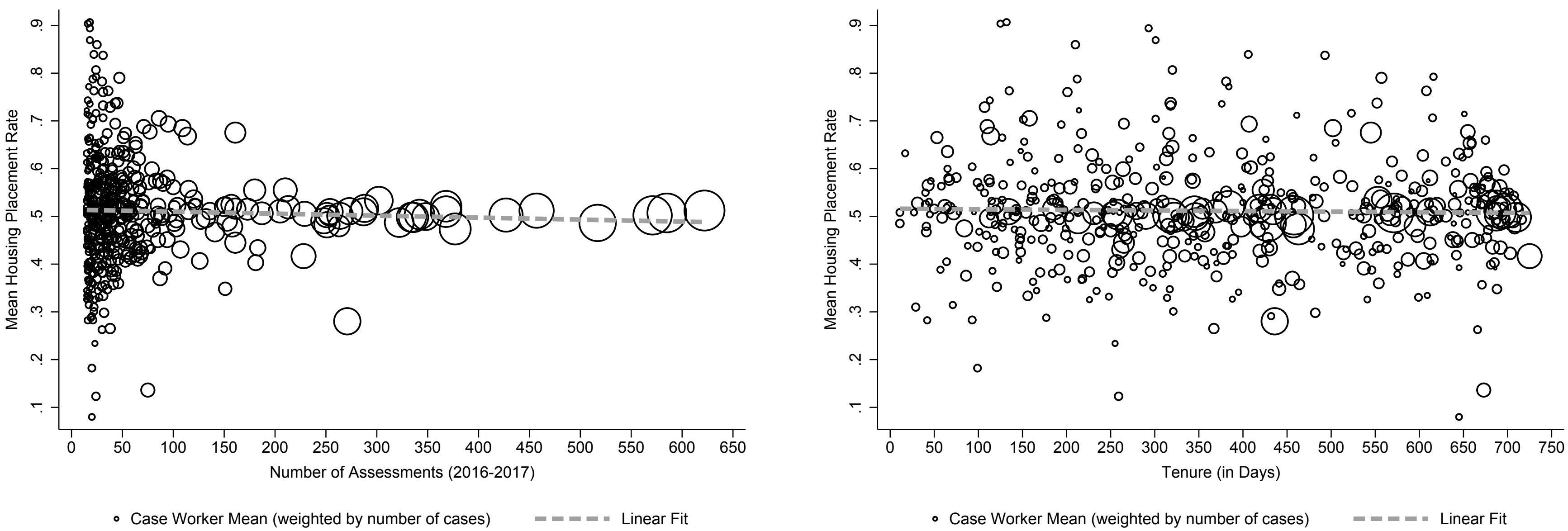
(c) Reported Permanent Housing Solution



(d) Reported No-Housing Solution

Figure B.1. Alternative Definitions of Recidivism to Homelessness Before and After Month of Intake.

Note: Instrument sample consisting of 39,119 non-veteran single adult cases assessed in 2016-2017. Cases are categorized in two groups, those receiving housing assistance within 18-months from intake date, as shown in solid black, or those not receiving housing assistance within this period, as shown in the dashed grey line. In panel (a), recidivism into homelessness is defined as enrolling in a street outreach program. In panel (b), recidivism into homelessness is defined by being assessed by a case worker at least once in each month. In panel (c), recidivism into homelessness is defined as reporting finding a permanent housing solution. In panel (d), recidivism into homelessness is defined as reporting no-housing solution.



(a) Number of Assessments

(b) Tenure

Figure B.2. Case Worker Housing Placement Rate versus Number of Assessments and Tenure

Note: Panel (a) plots case worker housing placement rate against the total number of assessments conducted by each case worker in 2016-2017. Panel (b) plots case worker housing placement rate against the proxy for tenure (in days) of each case worker. Tenure is defined as the number of days between the case worker's first and last observed assessments. There are 502 unique case workers, and on average, each case worker has handled a total of 60 assessments in 2016-2017. Housing placement rates are standardized by subtracting off service site by month of assessment means and case level covariates. Dot size is proportional to the number of cases the case worker has in the estimation sample, which is slightly smaller than the overall number of cases.

Table B.2. Sample Restrictions.

	Sample Sizes (Remaining after each restriction):			
	Number of Intakes	Number of Clients	Number of Case Workers	Number of Service Sites
	(1)	(2)	(3)	(4)
All Cases:	87,351	67,171	-	-
Keep all intakes conducted in 2016-2017	55,366	42,655	-	-
Keep individuals age 25-65	48,595	37,241	-	-
Drop cases with missing case worker, organization, or site information	47,157	36,620	3,028	350
Remove duplicates or multiple same-day intakes	46,411	36,511	3,020	348
Keep all non-veteran cases	39,116	30,794	2,580	316
Keep case workers with more than 15 non-veteran intakes	31,629	25,556	524	112
Keep service sites with at least 2 case workers in a given month	26,752	22,011	502	95

Note: The initial sample consists of all intakes processed in Los Angeles County's Coordinated Entry System in 2016-2018.

Table B.3. Summary Statistics.

	Estimation Sample	Instrument Sample	Excluded Sample
	(1)	(2)	(3)
Demographics:			
Age	45.12	45.24	45.50
	(11.23)	(11.22)	(11.20)
Female	0.342	0.359	0.396
	(0.474)	(0.480)	(0.489)
Black	0.509	0.484	0.429
	(0.500)	(0.500)	(0.495)
Hispanic	0.231	0.237	0.250
	(0.421)	(0.425)	(0.433)
White	0.195	0.209	0.238
	(0.396)	(0.406)	(0.426)
Acuity Assessment:			
Acuity Score (0-17)	7.267	7.511	8.040
	(3.710)	(3.711)	(3.660)
Homeless History	0.717	0.735	0.775
	(0.450)	(0.441)	(0.418)
Chronic Homeless	0.613	0.640	0.698
	(0.487)	(0.480)	(0.459)
Physical Disability	0.697	0.721	0.773
	(0.459)	(0.448)	(0.419)
Mental Disability	0.576	0.606	0.669
	(0.494)	(0.489)	(0.470)
Self Care Problems	0.291	0.293	0.297
	(0.454)	(0.455)	(0.457)
Used Crisis Service in Past 6 Months	0.0425	0.0445	0.0486
	(0.202)	(0.206)	(0.215)
Past Health, Criminal, Housing History:			
Any DHS Treatment in Past 12 Months	0.172	0.172	0.172
	(0.378)	(0.378)	(0.378)
Any DMH Treatment in Past 12 Months	0.116	0.116	0.116
	(0.321)	(0.320)	(0.320)
Any Substance Abuse Treatment in Past 12 Months	0.0846	0.0841	0.0831
	(0.278)	(0.278)	(0.276)
Involvement with Law Enforcement Agencies in Past 12 Months	0.137	0.136	0.134
	(0.343)	(0.343)	(0.341)
Received Emergency Cash Assistance in Past 12 Months	0.192	0.191	0.190
	(0.394)	(0.393)	(0.392)
Any Interaction with Homeless Support System in Past 12 Months	0.351	0.347	0.340
	(0.477)	(0.476)	(0.474)
Any Housing Assistance Received in Past 12 Months	0.282	0.276	0.263
	(0.450)	(0.447)	(0.440)
Number of Clients	22,011	30,794	11,346
Number of Cases	26,752	39,116	12,364

Note: Column 1 shows sample statistics for the estimation sample of intakes conducted in 2016-2017. Column 2 shows sample statistics for the instrument sample consisting of all non-veteran intakes, and column 3 shows sample statistics of all cases that are excluded from the estimation sample but are included in the instrument sample.

C Additional Results - Recidivism

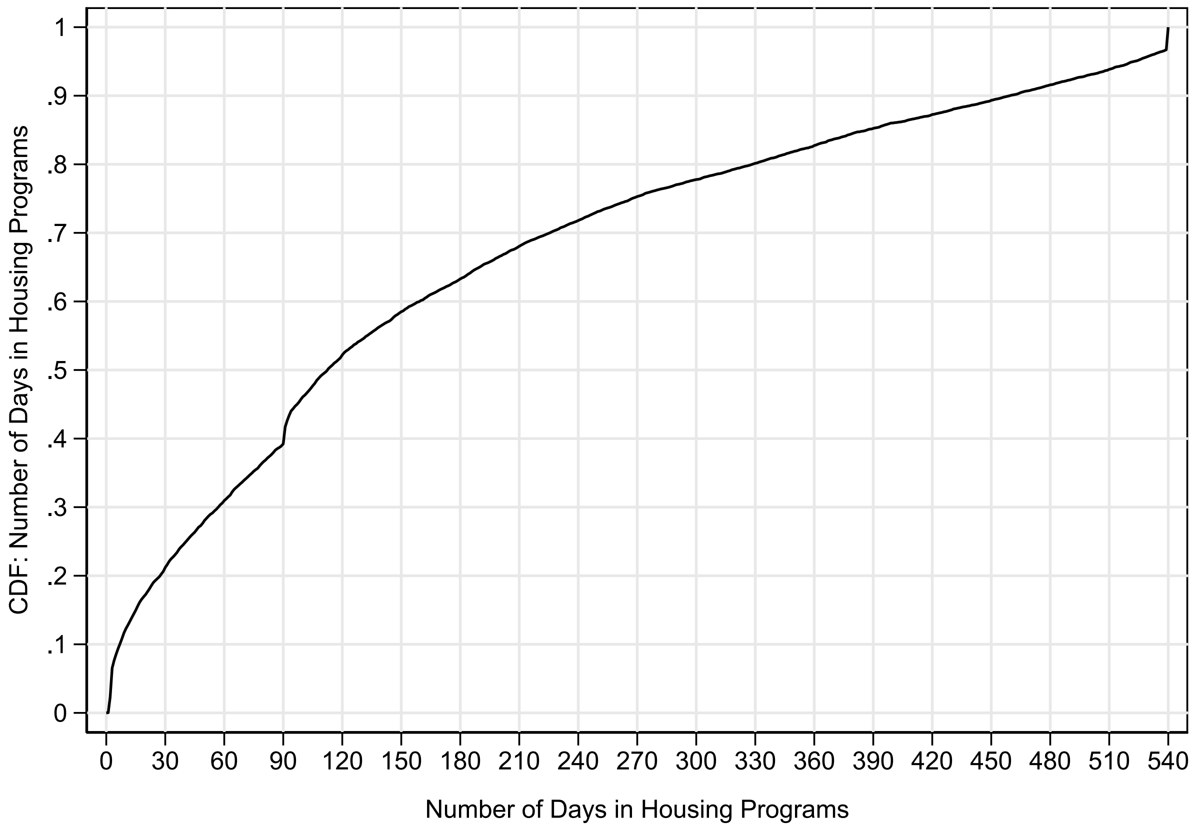
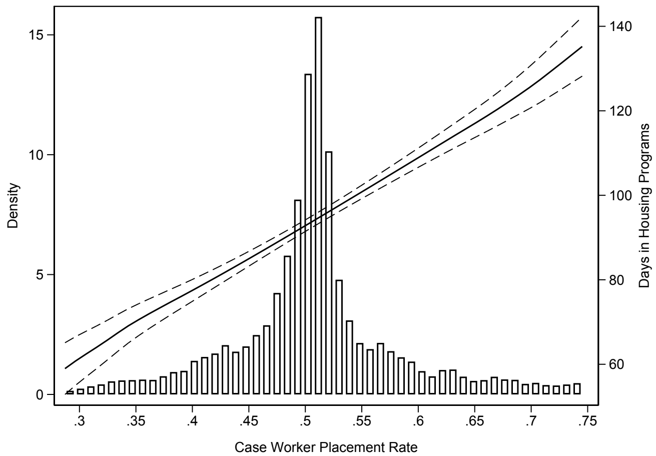
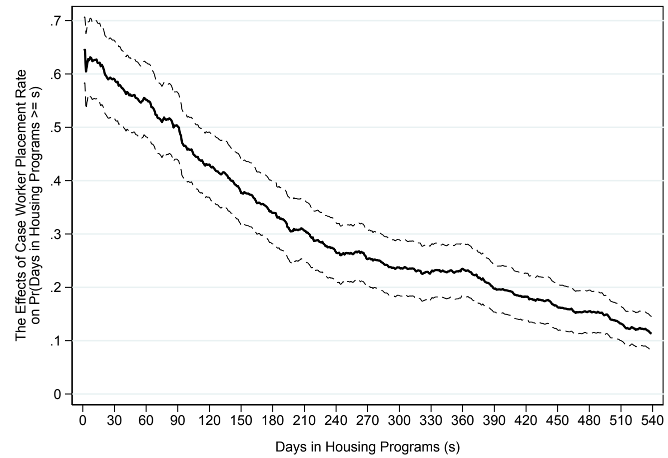


Figure C.1. Days in Housing Programs - CDF.

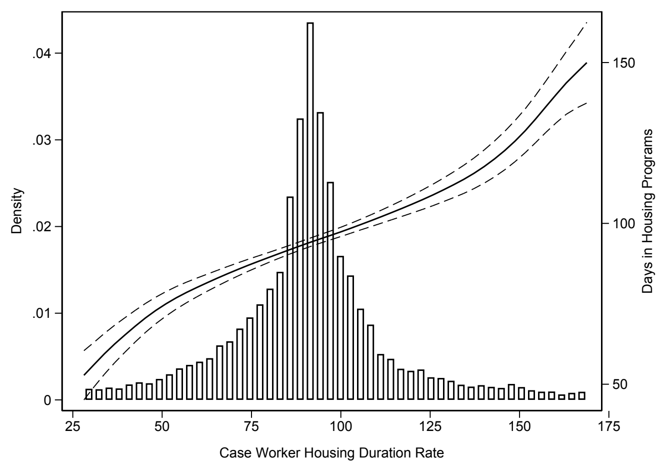
Note: Sample consists of 14,578 cases processed in 2016-2017 which resulted in any type of housing assistance.



(a) IV Estimates: No. of Returns to System – Months 1 to t



(b) Case Worker Placement Rate on Pr(Duration $\geq s$)



(c) Case Worker Housing Assistance Duration Rate on Housing Assistance Duration

Figure C.2. First Stage Graphs of Housing Assistance Duration on Case Worker Placement Rate.

Note: Estimation sample consisting of 26,752 assessments processed in 2016-2017. Days in housing programs is plotted on the right y-axis against leave-out mean case worker housing placement rate (panel (a)) and leave-out mean case worker housing assistance duration rate (panel (c)) of the assigned case worker shown along the x-axis. The plotted values are mean-standardized residuals from regressions on service site x month of assessment fixed effects and all variables listed in Table 1. The solid line shows a local linear regression of days in housing programs on case worker placement rate. The histograms in panels (a) and (c) show the density of case worker placement rate along the left y-axis (top and bottom 2% excluded). Panel (b) shows the estimates of case worker housing placement rate on Pr(Days in Housing Programs $\geq t$). Dashed lines show 90% confidence intervals.

Table C.1. Tests for the Monotonicity Assumption.

	Baseline Instrument	**Reverse-Sample Instrument**
	(1)	(2)
Dependent Variable	Pr(Received Housing Assistance)	
A. Housing Assistance Propensity (All Covariates)		
1. Sub-sample: Housing Assistance Propensity - 1st quartile (lowest)		
Estimate	0.718***	0.730***
(SE)	(0.0682)	(0.0862)
Dependent Mean	0.38	0.38
Number of Assessments	6,138	6,138
2. Sub-sample: Housing Assistance Propensity - 2nd quartile		
Estimate	0.669***	0.780***
(SE)	(0.0680)	(0.0811)
Dependent Mean	0.51	0.51
Number of Assessments	6,453	6,453
3. Sub-sample: Housing Assistance Propensity - 3rd quartile (highest)		
Estimate	0.720***	0.891***
(SE)	(0.0583)	(0.0695)
Dependent Mean	0.60	0.60
Number of Assessments	6,772	6,772
4. Sub-sample: Housing Assistance Propensity - 4th quartile (highest)		
Estimate	0.502***	0.635***
(SE)	(0.0594)	(0.0597)
Dependent Mean	0.69	0.69
Number of Assessments	6,686	6,686
B. Case Characteristics (Acuity Score)		
1. Sub-sample: Low Acuity Score (0-3)		
Estimate	0.726***	0.938***
(SE)	(0.131)	(0.143)
Dependent Mean	0.76	0.76
Number of Assessments	4,131	4,131
2. Sub-sample: Medium Acuity Score (4-7)		
Estimate	0.762***	0.897***
(SE)	(0.0498)	(0.0594)
Dependent Mean	0.58	0.58
Number of Assessments	10,461	10,431
3. Sub-sample: High Acuity Score (8-17)		
Estimate	0.472***	0.433***
(SE)	(0.0474)	(0.0501)
Dependent Mean	0.44	0.44
Number of Assessments	11,744	10,811
C. Chronic Homeless Status		
1. Sub-sample: Chronic Homeless		
Estimate	0.596***	0.481***
(SE)	(0.0449)	(0.0497)

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Table C.1 – continued from previous page

	Baseline Instrument	Reverse-Sample Instrument
	(1)	(2)
Dependent Variable	Pr(Received Housing Assistance)	
Dependent Mean	0.49	0.50
Number of Assessments	16,358	15,649
2. Sub-sample: Not Chronic Homeless		
Estimate	0.685***	0.735***
(SE)	(0.0575)	(0.0700)
Dependent Mean	0.63	0.63
Number of Assessments	10,205	10,184
D. Physical Disability		
1. Sub-sample: With Physical Disability		
Estimate	0.592***	0.505***
(SE)	(0.0427)	(0.0454)
Dependent Mean	0.51	0.51
Number of Assessments	18,634	17,434
2. Sub-sample: No Physical Disability		
Estimate	0.776***	0.890***
(SE)	(0.0584)	(0.0822)
Dependent Mean	0.63	0.63
Number of Assessments	7,926	7,926
E. Mental Disability		
1. Sub-sample: With Mental Disability		
Estimate	0.566***	0.497***
(SE)	(0.0498)	(0.0607)
Dependent Mean	0.50	0.52
Number of Assessments	15,364	13,573
2. Sub-sample: No Mental Disability		
Estimate	0.731***	0.777***
(SE)	(0.0664)	(0.0874)
Dependent Mean	0.61	0.61
Number of Assessments	11,238	11,238
F. Age		
1. Sub-sample: Age at Assesment < 47		
Estimate	0.648***	0.699***
(SE)	(0.0431)	(0.0510)
Dependent Mean	0.53	0.53
Number of Assessments	13,259	13,259
2. Sub-sample: Age at Assessment >= 47		
Estimate	0.664***	0.656***
(SE)	(0.0484)	(0.0595)
Dependent Mean	0.56	0.56
Number of Assessments	13,334	13,302
G. Gender		
1. Sub-sample: Males		
Estimate	0.675***	0.503***

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Table C.1 – continued from previous page

	Baseline Instrument	Reverse-Sample Instrument
	(1)	(2)
Dependent Variable	Pr(Received Housing Assistance)	
(SE)	(0.0468)	(0.0611)
Dependent Mean	0.53	0.49
Number of Assessments	17,539	15,818
2. Sub-sample: Females		
Estimate	0.611***	0.633***
(SE)	(0.0521)	(0.0698)
Dependent Mean	0.57	0.57
Number of Assessments	9,055	8,743
H. Race		
1. Sub-sample: Blacks		
Estimate	0.661***	0.673***
(SE)	(0.0492)	(0.0583)
Dependent Mean	0.62	0.62
Number of Assessments	13,511	13,381
2. Sub-sample: Not Blacks		
Estimate	0.622***	0.466***
(SE)	(0.0494)	(0.0615)
Dependent Mean	0.47	0.47
Number of Assessments	13,057	12,813
I. Ethnicity		
1. Sub-sample: Hispanics		
Estimate	0.542***	0.728***
(SE)	(0.0783)	(0.0857)
Dependent Mean	0.51	0.51
Number of Assessments	5,998	5,988
2. Sub-sample: Not Hispanics		
Estimate	0.658***	0.505***
(SE)	(0.0369)	(0.0597)
Dependent Mean	0.56	0.56
Number of Assessments	20,530	19,770

Note: Estimation sample of all assessments processed in 2016-2017. Controls include all variables listed in Table 1, including controls for service site x month of assessment FEs. Reverse-sample instrument is computed as the share of cases handled by the case worker that ended up receiving housing assistance in all other case types. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.2. Characterization of Compliers.

	Low Acuity	High Acuity
	(1)	(2)
1. Sub-sample: Housing Assistance Propensity - 1st quartile (lowest)		
Population Share	0.088	0.148
Complier Share	0.442	0.215
Complier Conditional Population Share	0.142	0.116
Complier Relative Likelihood	1.620	0.787
Number of Cases	2,351	3,957
2. Sub-sample: Housing Assistance Propensity - 2nd quartile		
Population Share	0.121	0.126
Complier Share	0.307	0.251
Complier Conditional Population Share	0.137	0.116
Complier Relative Likelihood	1.126	0.919
Number of Cases	3,246	3,383
3. Sub-sample: Housing Assistance Propensity - 3rd quartile		
Population Share	0.136	0.124
Complier Share	0.292	0.297
Complier Conditional Population Share	0.146	0.134
Complier Relative Likelihood	1.071	1.087
Number of Cases	3,643	3,310
4. Sub-sample: Housing Assistance Propensity - 4th quartile (highest)		
Population Share	0.119	0.138
Complier Share	0.263	0.194
Complier Conditional Population Share	0.114	0.098
Complier Relative Likelihood	0.963	0.710
Number of Cases	3,176	3,686

Note: Estimation sample of assessments processed in 2016-2017. I split the sample into eight mutually exclusive and collectively exhaustive subgroup based on acuity score (below and above 7) and quartiles of the predicted probability of housing assistance which is estimated based on all variables listed in Table 1. I estimate the first stage equation separately for each subgroup, which allows me to calculate the proportion of compliers by subgroup. For each subgroup, I report the population share (row 1), the complier share (row 2), and the probability of being in a subgroup conditional on being a complier (row 3). Finally, I also report the complier relative likelihood (row 4), which is the ratio of group-specific complier share to the overall complier share estimated to be 0.27 for the full estimation sample.

Table C.3. Quarterly Estimates of the Effect of Housing Assistance on Recidivism.

Time Period (Months after Assessment):	Months 1-3 (1)	Months 4-6 (2)	Months 7-9 (3)	Months 10-12 (4)	Months 13-15 (5)	Months 16-18 (6)
Dependent Variable:	**A. Pr(Ever Returned to Homeless System)**					
OLS: Housing Assistance	0.160***	0.106***	0.0924***	0.0742***	0.0586***	0.0479***
	(0.0104)	(0.00700)	(0.00668)	(0.00674)	(0.00593)	(0.00587)
RF: Housing Placement Rate	-0.0767***	-0.0567**	-0.0760***	-0.0522**	-0.0935***	-0.0958***
	(0.0268)	(0.0222)	(0.0235)	(0.0205)	(0.0187)	(0.0211)
2SLS: Housing Assistance	-0.119***	-0.0881**	-0.118***	-0.0810**	-0.145***	-0.149***
	(0.0429)	(0.0360)	(0.0394)	(0.0324)	(0.0314)	(0.0353)
Dependent Mean	0.17	0.13	0.12	0.11	0.10	0.10
Complier Dependent Mean if No Housing	0.23	0.13	0.17	0.14	0.12	0.10
Dependent Variable:	**B. Number of Times Returning to Homeless System**					
OLS: Housing Assistance	0.226***	0.124***	0.0876***	0.0640***	0.0381***	0.0230***
	(0.0168)	(0.00914)	(0.00803)	(0.00829)	(0.00594)	(0.00527)
RF: Housing Placement Rate	-0.113***	-0.0415	-0.0514**	-0.0131	-0.0774***	-0.0646***
	(0.0376)	(0.0298)	(0.0236)	(0.0194)	(0.0159)	(0.0163)
2SLS: Housing Assistance	-0.175***	-0.0644	-0.0797**	-0.0204	-0.120***	-0.100***
	(0.0601)	(0.0477)	(0.0386)	(0.0299)	(0.0269)	(0.0267)
Dependent Mean	0.24	0.12	0.09	0.08	0.06	0.06
Complier Dependent Mean if No Housing	0.30	0.12	0.09	0.08	0.09	0.04
Number of Assessments	26,752	26,752	26,752	26,752	26,752	26,752

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.4. The Effect of Housing Assistance on New Housing Assistance and Days Spent in Housing Programs in New Cases.

Dependent Variable:	Pr(Returned to Homeless Support System)	Pr(Housing Assistance in New Cases)	Pr(Housing Asisstance in New Cases | Returned to Homeless Support System)	Total Days in Housing Programs in New Cases
	(1)	(2)	(3)	(4)
RF: Case Worker Housing Placement Rate	-0.133***	0.00847	0.0563	8.455
	(0.0336)	(0.0219)	(0.0498)	(6.913)
IV: Housing Assistance	-0.206***	0.0132	0.137	13.13
	(0.0564)	(0.0339)	(0.119)	(10.55)
Dependent mean	0.36	0.12	0.24	28.59
Number of Assessments	26,752	26,752	5,965	26,752

Note: Estimation sample of assessments processed in 2016-2017. Controls include all controls listed in Table 1, including site x month of assessment fixed effects. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.5. The Effect of Housing Assistance for First-Time Users of Homeless Support System.

Dependent Variable:	**Pr(Ever Returned to Homeless System)**			**Number of Returns**
	Months 1-9 After Assessment (1)	Months 10-18 After Assessment (2)	Months 1-18 After Assessment (3)	Months 1-18 After Assessment (4)
OLS: Housing Assistance	0.234***	0.0988***	0.265***	0.545***
All Controls	(0.0140)	(0.0103)	(0.0157)	(0.0438)
RF: Housing Placement Rate	-0.132***	-0.0760**	-0.109**	-0.297***
All Controls	(0.0398)	(0.0302)	(0.0421)	(0.0885)
2SLS: Housing Assistance	-0.181***	-0.104**	-0.149**	-0.407***
All Controls	(0.0564)	(0.0424)	(0.0591)	(0.126)
Dependent Mean	0.23	0.14	0.30	0.50
Complier Mean if No Housing Assistance	0.32	0.19	0.32	0.62
Number of Assessments	15,146	15,146	15,146	15,146

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are clustered at the case worker level. *p<0.1, **p<0.05, ***p<0.01.

Table C.6. Heterogeneous Effects of Housing Assistance on Recidivism.

	OLS	2SLS
	(1)	(2)
Dependent Variable:	Pr(Returned to Homeless System)	
A. Housing Assistance Propensity (All Covariates)		
1. Sub-sample: Housing Assistance Propensity - Below Median		
Estimate	0.266***	-0.168**
(SE)	(0.0154)	(0.0719)
Dependent Mean	0.31	0.31
Number of Assessments	12,860	12,860
2. Sub-sample: Housing Assistance Propensity - Above Median		
Estimate	0.274***	-0.221***
(SE)	(0.0153)	(0.0831)
Dependent Mean	0.41	0.41
Number of Assessments	13,717	13,717
B. Case Characteristics (Acuity Score)		
1. Sub-sample: Below Median		
Estimate	0.294***	-0.113*
(SE)	(0.0172)	(0.0635)
Dependent Mean	0.36	0.36
Number of Assessments	14,825	14,825
2. Sub-sample: Above Median		
Estimate	0.251***	-0.332***
(SE)	(0.0142)	(0.107)
Dependent Mean	0.37	0.37
Number of Assessments	11,744	11,744
C. Chronic Homeless Status		
1. Sub-sample: Chronic Homeless		
Estimate	0.262***	-0.206***
(SE)	(0.0134)	(0.0696)
Dependent Mean	0.38	0.38
Number of Assessments	16,358	16,358
2. Sub-sample: Not Chronic Homeless		
Estimate	0.284***	-0.235***
(SE)	(0.0199)	(0.0824)
Dependent Mean	0.34	0.34
Number of Assessments	10,205	10,205
D. Physical Disability		
1. Sub-sample: With Physical Disability		
Estimate	0.267***	-0.252***
(SE)	(0.0135)	(0.0688)
Dependent Mean	0.38	0.38
Number of Assessments	18,634	18,634
2. Sub-sample: No Physical Disability		
Estimate	0.291***	-0.0748
(SE)	(0.0219)	(0.0651)
Dependent Mean	0.33	0.33

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Table C.6 – continued from previous page

	OLS	2SLS
	(1)	(2)
Dependent Variable:	Pr(Returned to Homeless System)	
Number of Assessments	7,926	7,926
E. Mental Disability		
1. Sub-sample: With Mental Disability		
Estimate	0.272***	-0.263***
(SE)	(0.0133)	(0.0766)
Dependent Mean	0.38	0.38
Number of Assessments	15,364	15,364
2. Sub-sample: No Mental Disability		
Estimate	0.271***	-0.123
(SE)	(0.0181)	(0.0811)
Dependent Mean	0.33	0.33
Number of Assessments	11,238	11,238
F. Age		
1. Sub-sample: Age at Assesment < 47		
Estimate	0.266***	-0.124*
(SE)	(0.0162)	(0.0724)
Dependent Mean	0.33	0.33
Number of Assessments	13,259	13,259
2. Sub-sample: Age at Assessment >= 47		
Estimate	0.273***	-0.277***
(SE)	(0.0151)	(0.0760)
Dependent Mean	0.39	0.39
Number of Assessments	13,334	13,334
G. Gender		
1. Sub-sample: Males		
Estimate	0.279***	-0.188***
(SE)	(0.0152)	(0.0601)
Dependent Mean	0.35	0.35
Number of Assessments	17,539	17,539
2. Sub-sample: Females		
Estimate	0.254***	-0.238***
(SE)	(0.0156)	(0.0914)
Dependent Mean	0.39	0.39
Number of Assessments	9,055	9,055
H. Race		
1. Sub-sample: Blacks		
Estimate	0.291***	-0.223***
(SE)	(0.0171)	(0.0682)
Dependent Mean	0.39	0.39
Number of Assessments	13,511	13,511
2. Sub-sample: Hispanics		
Estimate	0.246***	-0.00375
(SE)	(0.0215)	(0.144)
Dependent Mean	0.33	0.33

(continued on next page)

Table C.6 – continued from previous page

	OLS	2SLS
	(1)	(2)
Dependent Variable:	Pr(Returned to Homeless System)	
Number of Assessments	5,998	5,998
3. Sub-sample: Whites		
Estimate	0.239***	-0.315***
(SE)	(0.0195)	(0.118)
Dependent Mean	0.36	0.36
Number of Assessments	5,034	5,034

Note: Estimation sample of all assessments processed in 2016-2017. Controls include all variables listed in Table 1, including controls for service site x month of assessment FEs. Dependent variable in all specifications is an indicator for whether an individual returned at least once to the homeless support system by 18 months after intake. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.7. Summary Measures of Treatment Effects Based on the 2SLS and the MTE.

A. Treatment Parameters Based on the 2SLS	**Local Average Treatment Effect (LATE) for the estimation sample** (1)	**Local Average Treatment Effect (LATE) for the Common Support Sample** (2)
Pr(Returned to Homeless Support System)	-0.206***	-0.144***
	(0.0564)	(0.0482)
Number of Assessments	26,752	26,484

B. Treatment Parameters Based on the MTE for the Common Support Sample	**Average Treatment Effect on the Treated (ATT)** (1)	**Average Treatment Effect (ATE)** (2)	**Average Treatment Effect on the Untreated (ATUT)** (3)
1. Linear Specification			
Pr(Returned to Homeless Support System)	-0.1771*	-0.130**	-0.073
	(0.0977)	(0.0637)	(0.0956)
2. Global Quadratic Polynomial			
Pr(Returned to Homeless Support System)	-0.178*	-0.131*	-0.074
	(0.1002)	(0.0688)	(0.1005)
3. Global Cubic Polynomial			
Pr(Returned to Homeless Support System)	-0.185**	-0.132***	-0.069
	(0.0816)	(0.05)	(0.0707)
4. Global Quartic Polynomial			
Pr(Returned to Homeless Support System)	-0.215**	-0.163**	-0.100
	(0.1016)	(0.0691)	(0.1006)
Number of Cases	26,484	26,484	26,484

Note: Full sample of assessments processed in 2016-2017 and trimmed sample with common support (1%). The rescaled treatment parameters are weighted averages (for the treated (ATT), for all (ATE), and for the untreated (ATUT)) over the MTE curves over the area with common support (weights sum to 1) Standard errors are constructed based on 100 non-parametric bootstrap replications. *p<0.1, **p<0.05, ***p<0.01.

Table C.8. The Effect of Case Workers Housing Placement Rate on Various Case Worker Treatment Margins.

	Temporary vs. Permanent Housing		**Duration of Housing Assistance**		**Non-Housing Services**
	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Pr(Permanent Housing)	Pr(Temporary Housing)	No. of Days in Any Housing Program	Average Time to Housing Assistance Treatment (in Days)	Pr(Received Non-Housing Services)
Housing Placement Rate	0.408***	0.318***	164.9***	-188.3***	-0.100
	(0.0631)	(0.0867)	(14.12)	(15.09)	(0.0730)
Dependent mean	0.193	0.427	94.68	107.862	0.343
Number of Assessments	26,752	26,752	26,752	26,752	26,752

Note: All specifications include site x month of assessment fixed effects and all of the controls listed in Table 1. The estimates present the reduced-form estimates of case worker housing placement rate. In column 5, average time to housing assistance is defined as the mean number of days passed from assessment date to first housing program enrollment, at the case worker level. In column 6, the outcome variable is a binary variable equal to one if the individual was enrolled at least once in a non-housing services program since assessment date, and zero otherwise. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.9. Balancing Tests of Temporary and Permanent Housing Instruments.

	Permanent Housing			Temporary Housing		
	Received	Placement Rate	Placement Rate Above Median	Received	Placement Rate	Placement Rate Above Median
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics:						
Age	0.000827***	-0.000147**	0.000138	-0.000321	0.0001	0.000284
	(0.000261)	(0.0001)	(0.000286)	(0.000281)	(0.0001)	(0.000284)
Female	0.0392***	0.00800***	-0.0129	-0.0226***	-0.00554*	-0.00911
	(0.00708)	(0.00281)	(0.0337)	(0.00698)	(0.00282)	(0.0271)
Black	0.0985***	0.00744**	0.0299*	0.0434***	-0.0001	0.00424
	(0.0122)	(0.00333)	(0.0179)	(0.0121)	(0.00328)	(0.0153)
Hispanic	0.0485***	0.00276	0.0237	0.0538***	0.00362	-0.000939
	(0.0120)	(0.00283)	(0.0177)	(0.0122)	(0.00351)	(0.0150)
White	0.0542***	0.00265	0.0185	0.0407***	0.00236	-0.000325
	(0.0124)	(0.00321)	(0.0184)	(0.0128)	(0.00374)	(0.0161)
Acuity Assessment:						
Acuity Score (0-18)	-0.000955	-0.000217	0.00369	0.00211	-0.000880	-0.00278
	(0.00143)	(0.000808)	(0.00337)	(0.00131)	(0.000709)	(0.00293)
Homeless History	-0.0199*	0.00598**	0.0152	-0.00765	-0.00810***	-0.0209
	(0.0104)	(0.00299)	(0.0137)	(0.00913)	(0.00265)	(0.0161)
Chronic Homeless	0.00277	-0.00563*	-0.00510	-0.00304	0.00566**	0.0152
	(0.0108)	(0.00314)	(0.0132)	(0.00935)	(0.00254)	(0.0148)
Physical Disability	0.000800	-0.000660	-0.00539	-0.00484	0.00236	0.000831
	(0.00663)	(0.00224)	(0.0112)	(0.00680)	(0.00190)	(0.0110)
Mental Disability	-0.00721	-0.00423**	0.00306	0.00695	0.00471**	0.0196*
	(0.00710)	(0.00182)	(0.0142)	(0.00731)	(0.00239)	(0.0112)
Self Care Problems	0.00109	-0.00601*	-0.0342	-0.0142**	-0.00002	0.00102
	(0.00695)	(0.00333)	(0.0209)	(0.00682)	(0.00339)	(0.0195)
Used Crisis Service in Past 6 Months	0.000682	-0.00131	0.00883	-0.0177	0.00552	0.0246
	(0.0134)	(0.00433)	(0.0191)	(0.0124)	(0.00361)	(0.0198)
Past Health, Criminal, Housing History:						
Any DHS Treatment in Past 12 Months	-0.0114	-0.000261	-0.00564	0.0216***	0.00161	0.0133*
	(0.00843)	(0.00165)	(0.00668)	(0.00831)	(0.00149)	(0.00714)
Any DMH Treatment in Past 12 Months	-0.00594	-0.000865	-0.00133	0.00573	0.000564	-0.00782
	(0.00981)	(0.00167)	(0.00916)	(0.00948)	(0.00153)	(0.00937)
Any Substance Abuse Treatment in Past 12 Months	-0.0111	0.00179	0.0147	0.00999	0.00143	-0.00978
	(0.0112)	(0.00189)	(0.00897)	(0.0103)	(0.00175)	(0.00880)
Involvement with Law Enforcement Agencies in Past 12 Months	-0.00646	0.00251	0.00598	-0.00672	-0.00357**	-0.00379
	(0.0101)	(0.00182)	(0.00896)	(0.00913)	(0.00172)	(0.00895)
Received Emergency Cash Assistance in Past 12 Months	0.00860	-0.000957	0.00630	-0.00554	0.00141	0.00143
	(0.00787)	(0.00156)	(0.00732)	(0.00889)	(0.00168)	(0.00750)
Any Interaction with Homeless Support System in Past 12 Months	0.0220*	0.00291	0.00339	-0.00264	-0.00226	-0.0189*
	(0.0125)	(0.00254)	(0.0113)	(0.0125)	(0.00211)	(0.0112)
Any Housing Assistance Received in Past 12 Months	-0.0152	-0.00333	0.0122	0.0828***	0.00765***	0.0299**
	(0.0136)	(0.00342)	(0.0126)	(0.0134)	(0.00272)	(0.0124)
F-statistic for joint test	7.802	1.667	1.463	7.113	1.372	1.280
p-value	0.000	0.038	0.093	0.000	0.134	0.191
Number of Cases	26,752					

Note: Columns 1-6 show estimates for estimation sample of individuals assessed in 2016-2017. All estimations include controls for site x month of assessment FEs. Reported F-statistic refers to a joint test of the null hypothesis for all variables. The omitted category for race is missing/multiple/other race. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.10. The Effect of Number of Days in Housing Programs on Recidivism.

Dependent Variable:	**Pr(Ever Returned to Homeless System)**			**Number of Returns to Homeless System**
Time Period (Months After Assessment):	Months 1-9 (1)	Months 10-18 (2)	Months 1-18 (3)	Months 1-18 (4)
OLS: Days in Housing Programs (in 250s)	0.159***	0.0435***	0.154***	0.343***
All Controls	(0.00852)	(0.00680)	(0.00889)	(0.0273)
RF: Housing Placement Rate	-0.108***	-0.131***	-0.133***	-0.361***
All Controls	(0.0325)	(0.0266)	(0.0336)	(0.0712)
2SLS: Days in Housing Programs (in 250s)	-0.203***	-0.199***	-0.202***	-0.547***
All Controls	(0.0679)	(0.0419)	(0.0506)	(0.112)
Dependent Mean	0.28	0.18	0.36	0.64
Number of Assessments	26,752	26,752	26,752	26,752

Note: Estimation sample of all assessments in 2016-2017. The estimates show the effect of an increase in duration of housing assistance by 250 days. All specifications include service site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.11. Controlling for Case Worker Rates in Treatment Margins other than Housing Assistance.

	First Stage	Reduced Form		IV	
	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	**Pr(Received Housing Assistance)**	**Pr(Returned to Homeless System)**	**No. of times returned to Homeless System**	**Pr(Returned to Homeless System)**	**No. of times returned to Homeless System**
A. Baseline Specification					
	0.644***	-0.133***	-0.361***	-0.206***	-0.560***
	(0.0377)	(0.0336)	(0.0712)	(0.0564)	(0.125)
F-stat (Instrument)	292.22				
B. Controls for Non-Housing Services Placement Rate					
	0.641***	-0.131***	-0.356***	-0.204***	-0.556***
	(0.0369)	(0.0330)	(0.0705)	(0.0560)	(0.125)
F-stat (Instrument)	301.79				
C. Controls for Non-Housing Services Placement Rate and Housing Assistance Duration Rate					
	0.571***	-0.0439	-0.191*	-0.0770	-0.334*
	(0.0585)	(0.0493)	(0.107)	(0.0883)	(0.200)
F-stat (Instrument)	95.33				
Number of Assessments	26,752	26,752	26,752	26,752	26,752

Note: Estimation sample of all assessments in 2016-2017. All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.12. IV Model with Three Treatment Options ‘Housing Assistance’, ‘Duration of Housing Asistance (in Days)’, and ‘Non-Housing Treatment or No Treatment’.

	First Stages		**Reduced Form**			**IV**	
	(1)	(2)	(3)	(4)		(5)	(6)
	Outcome: **Pr(Housing Assistance)**	Outcome: **Days in Housing Programs (in 250s)**	Months 1-18 after Assessment **Pr(Returned to Homeless Support System)**	Months 1-18 after Assessment **Number of returns to Homeless Support System**		Months 1-18 after Assessment **Pr(Returned to Homeless Support System)**	Months 1-18 after Assessment **Number of returns to Homeless Support System**
A. Baseline Specification							
Instrument:					Outcome:		
Housing Placement Rate	0.644***		-0.133***	-0.361***	Housing Assistance	-0.206***	-0.560***
	(0.0377)		(0.0336)	(0.0712)		(0.0564)	(0.125)
F-stat (Instrument)	292.22						
Dependent Mean	0.5449		0.3623	0.6432		0.3623	0.6432
B. Specification with Three Treatment Options							
Instruments:					Outcomes:		
Housing Placement Rate	0.574***	0.209***	-0.0456	-0.194*	Housing Assistance	-0.00962	-0.217
	(0.0594)	(0.0614)	(0.0502)	(0.111)		(0.127)	(0.287)
Housing Assistance Duration Rate	0.0739**	0.473***	-0.0915**	-0.175**	Housing Days (250s days)	-0.192*	-0.335
	(0.0352)	(0.0671)	(0.0432)	(0.0853)		(0.112)	(0.236)
SW F-stat (Instrument)	35.17	31.45					
Dependent Mean	0.5449	0.3787	0.3623	0.6432		0.3623	0.6432
Number of Assessments	26,752	26,752	26,752	26,752		26,752	26,752

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.13. Specification Checks - Minimum Number of Cases per Case Workers

	Baseline	Cases Handled by Case Worker in Sample			
	Baseline (1)	≥ 10 Cases (2)	≥ 20 Cases (3)	≥ 30 Cases (4)	≥ 40 Cases (5)
Dependent Variable:	**A. Pr(Received Housing Assistance)**				
First Stage: Case Worker Housing Placement Rate	0.644***	0.609***	0.661***	0.664***	0.684***
	(0.0377)	(0.0351)	(0.0411)	(0.0508)	(0.0605)
Dependent Mean	0.5449	0.5419	0.5512	0.5559	0.5664
Dependent Variable (Months 1-18 after Assessment):	**B. Pr(Returned to Homeless Support System)**				
RF: Case Worker Housing Placement Rate	-0.133***	-0.118***	-0.136***	-0.146***	-0.134***
	(0.0336)	(0.0308)	(0.0366)	(0.0447)	(0.0484)
IV: Housing Assistance	-0.206***	-0.194***	-0.206***	-0.220***	-0.196**
	(0.0564)	(0.0536)	(0.0599)	(0.0746)	(0.0805)
Dependent Mean	0.36	0.36	0.36	0.36	0.36
Dependent Variable (Months 1-18 after Assessment):	**C. Number of Times Returning to Homeless Support System**				
RF: Case Worker Housing Placement Rate	-0.361***	-0.334***	-0.344***	-0.376***	-0.346***
	(0.0712)	(0.0655)	(0.0771)	(0.0916)	(0.0943)
IV: Housing Assistance	-0.560***	-0.549***	-0.521***	-0.565***	-0.506***
	(0.125)	(0.120)	(0.131)	(0.161)	(0.168)
Dependent Mean	0.64	0.64	0.64	0.65	0.65
Number of Assessments	26,752	28,309	25,386	23,340	20,873

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.14. Specification Checks - Fixed Effects Selection.

		Fixed Effects Selection			
	Baseline (1)	Site x Quarter (2)	Site x Year (3)	Provider x Month (4)	SPA x Month (5)
Dependent Variable:		**A. Pr(Received Housing Assistance)**			
First Stage: Case Worker Housing Placement Rate	0.644***	0.593***	0.571***	0.647***	0.577***
	(0.0377)	(0.0414)	(0.0467)	(0.0477)	(0.0910)
Dependent Mean	0.5449	0.5356	0.5328	0.5323	0.5297
Dependent Variable (Months 1-18 after Assessment):		**B. Pr(Returned to Homeless Support System)**			
RF: Case Worker Housing Placement Rate	-0.133***	-0.130***	-0.130***	-0.124***	-0.123**
	(0.0336)	(0.0320)	(0.0344)	(0.0342)	(0.0486)
IV: Housing Assistance	-0.206***	-0.219***	-0.227***	-0.192***	-0.213**
	(0.0564)	(0.0580)	(0.0630)	(0.0568)	(0.106)
Dependent Mean	0.36	0.36	0.36	0.36	0.36
Dependent Variable (Months 1-18 after Assessment):		**C. Number of Times Returning to Homeless Support System**			
RF: Case Worker Housing Placement Rate	-0.361***	-0.326***	-0.322***	-0.352***	-0.327***
	(0.0712)	(0.0674)	(0.0725)	(0.0735)	(0.0933)
IV: Housing Assistance	-0.560***	-0.549***	-0.564***	-0.544***	-0.567***
	(0.125)	(0.126)	(0.135)	(0.127)	(0.217)
Dependent Mean	0.64	0.64	0.63	0.63	0.63
Number of Assessments	26,752	29,422	30,343	28,788	30,393

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.15. Specification Checks - Treatment Timing Definition.

		Treatment Definition: Received Housing Assistance Within:			
	Baseline	1 Month	3 Months	6 Months	12 Months
	(1)	(2)	(3)	(4)	(5)
Dependent Variable:		**A. Pr(Received Housing Assistance)**			
First Stage: Case Worker Housing Placement Rate	0.644***	0.859***	0.788***	0.735***	0.682***
	(0.0377)	(0.0264)	(0.0298)	(0.0317)	(0.0345)
Dependent Mean	0.5449	0.3615	0.4160	0.4601	0.5157
Dependent Variable (Months 1-18 after Assessment):		**B. Pr(Returned to Homeless Support System)**			
RF: Case Worker Housing Placement Rate	-0.133***	-0.0992***	-0.104***	-0.120***	-0.130***
	(0.0336)	(0.0288)	(0.0299)	(0.0311)	(0.0327)
IV: Housing Assistance	-0.206***	-0.116***	-0.133***	-0.164***	-0.190***
	(0.0564)	(0.0349)	(0.0393)	(0.0443)	(0.0507)
Dependent Mean	0.36	0.36	0.36	0.36	0.36
Dependent Variable (Months 1-18 after Assessment):		**C. Number of Times Returning to Homeless Support System**			
RF: Case Worker Housing Placement Rate	-0.361***	-0.215***	-0.241***	-0.293***	-0.353***
	(0.0712)	(0.0610)	(0.0621)	(0.0656)	(0.0693)
IV: Housing Assistance	-0.560***	-0.250***	-0.306***	-0.398***	-0.518***
	(0.125)	(0.0748)	(0.0831)	(0.0957)	(0.112)
Dependent Mean	0.64	0.64	0.64	0.64	0.64
Number of Assessments	26,752	26,752	26,752	26,752	26,752

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.16. Specification Checks -Instrument Definition.

		Instrument Definition:			
	Baseline	Winsorized Instrument	Split Sample	with Veteran Cases	Residualized Placement Rate
	(1)	(2)	(3)	(4)	(5)
Dependent Variable:		**A. Pr(Received Housing Assistance)**			
First Stage: Case Worker Housing Placement Rate	0.644***	0.666***	0.613***	0.657***	0.713***
	-0.0377	(0.0419)	(0.0461)	(0.0377)	(0.0435)
Dependent Mean	0.5449	0.5449	0.5504	0.5449	0.5449
Dependent Variable (Months 1-18 after Assessment):		**B. Pr(Returned to Homeless Support System)**			
RF: Case Worker Housing Placement Rate	-0.133***	-0.141***	-0.100**	-0.129***	-0.150***
	(0.0336)	(0.0359)	(0.0410)	(0.0342)	(0.0389)
IV: Housing Assistance	-0.206***	-0.212***	-0.164**	-0.196***	-0.211***
	(0.0564)	(0.0582)	(0.0671)	(0.0557)	(0.0592)
Dependent Mean	0.36	0.36	0.36	0.36	0.36
Dependent Variable (Months 1-18 after Assessment):		**C. Number of Times Returning to Homeless Support System**			
RF: Case Worker Housing Placement Rate	-0.361***	-0.384***	-0.304***	-0.357***	-0.409***
	(0.0712)	(0.0760)	(0.0799)	(0.0726)	(0.0821)
IV: Housing Assistance	-0.560***	-0.577***	-0.497***	-0.543***	-0.574***
	(0.125)	(0.130)	(0.138)	(0.124)	(0.132)
Dependent Mean	0.64	0.64	0.64	0.64	0.64
Number of Assessments	26,752	26,752	13,394	26,752	26,752

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table C.17. IV Model with Three Treatment Options: 'Housing Assistance', 'Non-Housing Services', and 'No Treatment'.

	First Stages		Reduced Form			IV	
	(1)	(2)	(3)	(4)		(5)	(6)
	Outcome: **Pr(Housing Assistance)**	Outcome: **Pr(Non-Housing Assistance)**	Months 1-18 after Assessment **Pr(Returned to Homeless Support System)**	Months 1-18 after Assessment **Number of returns**		Months 1-18 after Assessment **Pr(Returned to Homeless Support System)**	Months 1-18 after Assessment **Number of returns**
A. Baseline Specification							
Instrument:					Outcome:		
Housing Placement Rate	0.644***		-0.133***	-0.361***	Housing Assistance	-0.206***	-0.560***
	(0.0377)		(0.0336)	(0.0712)		(0.0564)	(0.125)
F-stat (Instrument)	292.22						
Dependent Mean	0.5449		0.3623	0.6432		0.3623	0.6432
B. Specification with Three Treatment Options							
Instruments:					Outcomes:		
Housing Placement Rate	0.641***	-0.0715**	-0.131***	-0.356***	Housing Assistance	-0.199***	-0.546***
	(0.0369)	(0.0279)	(0.0330)	(0.0705)		(0.0559)	(0.126)
Non-Housing Services Placement Rate	-0.0775***	0.671***	0.0476	0.105*	Non-Housing Services	0.0479	0.0931
	(0.0267)	(0.0419)	(0.0291)	(0.0582)		(0.0456)	(0.0962)
SW F-stat (Instrument)	258.85	243.4					
Dependent Mean	0.5449	0.3426	0.3623	0.6432		0.3623	0.6432
Number of Assessments	26,752	26,752	26,752	26,752		26,752	26,752

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

D Additional Results - Economic and Social Outcomes

Table D.1. First Stage and Recidivism Estimates by Sub-Sample.

Sample:	(1) Baseline	(2) DHS	(3) DPH	(4) DMH, Sheriff, Probation and General Relief	(5) Employment, SSI and SSDI Sample	(6) Income	(7) Food Stamps
I. Balancing Tests							
F-statistic for joint test of covariates	1.12	0.99	1.24	1.46	1.07	1.07	1.15
p-value	0.33	0.47	0.23	0.09	0.37	0.37	0.29
II. First Stage: Pr(Received Housing Assistance)							
Housing Placement Rate	0.644***	0.598***	0.541***	0.633***	0.627***	0.613***	0.592***
	(0.0377)	(0.0440)	(0.0803)	(0.0381)	(0.0382)	(0.0398)	(0.0407)
F-stat. (Instrument)	292.22	184.88	45.35	275.82	268.92	237.42	211.76
Dependent mean	0.545	0.575	0.543	0.578	0.623	0.630	0.643
Number of Assessments	26,752	11,339	5,314	15,510	23,387	23,054	18,773
III. 2SLS: Pr(Return to Homeless Support System - Months 1 to 18)							
Housing Assistance	-0.206***	-0.242***	-0.242	-0.230***	-0.323***	-0.325***	-0.317***
	(0.0564)	(0.0831)	(0.148)	(0.0646)	(0.0639)	(0.0664)	(0.0691)
Dependent mean	0.362	0.440	0.458	0.418	0.405	0.402	0.424
Number of Assessments	26,752	11,339	5,314	15,510	23,387	23,054	18,773

Note: Columns 1-7 show the main results on recidivism into homelessness for the different sub-samples used in the analysis. All specifications include service site x month of assessment fixed effects. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table D.2. The Effect of Housing Assistance on Department of Health Services.

Dependent Variable :	Any Treatment (1)	Inpatient (2)	Outpatient (3)	Emergency (4)
A. Ever Received (1-18 Months after Assessment):				
OLS: Housing Assistance	0.00249	0.00268	0.00707	0.00159
All Controls	(0.00739)	(0.00310)	(0.00529)	(0.00619)
RF: Housing Placement Rate	-0.0367*	0.0242**	-0.0285	-0.0323*
All Controls	(0.0220)	(0.0120)	(0.0207)	(0.0178)
2SLS: Housing Assistance	-0.0613*	0.0405*	-0.0476	-0.0541*
All Controls	(0.0370)	(0.0206)	(0.0347)	(0.0302)
Dependent Mean	0.10	0.02	0.05	0.06
Number of Assessments	11,339	11,339	11,339	11,339
B. Number of Days/Episodes (1-18 Months after Assessment):				
OLS: Housing Assistance	0.0195	0.0672	0.0268	-0.0124
All Controls	(0.0729)	(0.0862)	(0.0629)	(0.0237)
RF: Housing Placement Rate	-0.0417	0.573*	-0.0202	-0.0817
All Controls	(0.230)	(0.329)	(0.188)	(0.0851)
2SLS: Housing Assistance	-0.0697	0.958*	-0.0338	-0.137
All Controls	(0.384)	(0.562)	(0.314)	(0.143)
Dependent Mean	0.50	0.27	0.33	0.14
Number of Assessments	11,339	11,339	11,339	11,339

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table D.3. The Effect of Housing Assistance on Mental Health Services.

Dependent Variable:	Any Treatment (1)	Inpatient/Residential (2)	Outpatient (3)
A. Ever Received (1-18 Months after Assessment):			
OLS: Housing Assistance	-0.00539	-0.00339*	-0.00463
All Controls	(0.00380)	(0.00200)	(0.00367)
RF: Housing Placement Rate	-0.0292**	-0.00471	-0.0212
All Controls	(0.0136)	(0.00717)	(0.0131)
2SLS: Housing Assistance	-0.0460**	-0.00744	-0.0334
All Controls	(0.0218)	(0.0114)	(0.0208)
Dependent Mean	0.03	0.01	0.028
Complier Mean if No Housing Assistance	0.07	0.00	0.06
Number of Assessments	15,510	15,510	15,510
B. Number of Days/Episodes (1-18 Months after Assessment):			
OLS: Housing Assistance	-0.0211	-0.103	-0.0173
All Controls	(0.130)	(0.523)	(0.129)
RF: Housing Placement Rate	-0.809	-2.005*	-0.788
All Controls	(0.502)	(1.112)	(0.501)
2SLS: Housing Assistance	-1.278	-3.165*	-1.244
All Controls	(0.809)	(1.803)	(0.806)
Dependent Mean	0.38	1.14	0.36
Complier Mean if No Housing Assistance	1.75	3.55	1.73
Number of Assessments	15,510	15,510	15,510

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table D.4. The Effect of Housing Assistance on Substance Abuse Treatments.

Dependent Variable:	Any Treatment (1)	Detox (2)	Residential (3)	Outpatient (4)
A. Ever Received (1-18 Months after Assessment):				
OLS: Housing Assistance	0.00388	0.00330	0.00154	-0.000366
All Controls	(0.00388)	(0.00212)	(0.00305)	(0.00283)
RF: Housing Placement Rate	-0.00363	0.00460	-0.00569	-0.0152
All Controls	(0.0171)	(0.0108)	(0.0142)	(0.00999)
2SLS: Housing Assistance	-0.00671	0.00851	-0.0105	-0.0282
All Controls	(0.0316)	(0.0200)	(0.0264)	(0.0191)
Dependent Mean	0.01	0.00	0.007	0.01
Complier Dependent Mean if No Housing Assistance	0.01	0.00	0.03	0.03
Number of Assessments	5,314	5,314	5,314	5,314
B. Number of Days/Episodes:				
OLS: Housing Assistance	0.00753	0.722	1.387	-0.00316
All Controls	(0.0116)	(0.448)	(1.054)	(0.00696)
RF: Housing Placement Rate	-0.0723	0.480	0.143	-0.0568**
All Controls	(0.0473)	(2.780)	(5.274)	(0.0222)
2SLS: Housing Assistance	-0.134	0.887	0.265	-0.105**
All Controls	(0.0878)	(5.154)	(9.755)	(0.0423)
Dependent Mean	0.04	0.53	2.07	0.01
Complier Dependent Mean if No Housing Assistance	0.12	0.53	10.68	0.08
Number of Assessments	5,314	5,314	5,314	5,314

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table D.5. The Effect of Housing Assistance on Criminal Activity.

Dependent Variable :	Jail Bookings (1)	Jail Days (2)	At least One Crime (3)	Number of Crimes (4)	Probation Service (5)	Probation Days (6)
OLS: Housing Assistance	0.217*	1.429*	0.00749	0.0332	0.00329	0.0475
All Controls	(0.111)	(0.789)	(0.00509)	(0.0348)	(0.00362)	(0.143)
RF: Housing Placement Rate	-0.955**	-8.457***	-0.0501***	-0.247**	-0.0230	-0.351
All Controls	(0.389)	(2.503)	(0.0164)	(0.115)	(0.0166)	(0.702)
2SLS: Housing Assistance	-1.507**	-13.35***	-0.0790***	-0.389**	-0.0363	-0.555
All Controls	(0.621)	(4.001)	(0.0260)	(0.182)	(0.0261)	(1.109)
Dependent Mean	1.05	6.45	0.07	0.31	0.033	1.17
Complier Dependent Mean if No Housing Assistance	1.09	10.70	0.10	0.22	0.08	1.67
Number of Assessments	15,510	15,510	15,510	15,510	15,510	15,510

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table D.6. The Effect of Housing Assistance on Income, Employment and Social Benefits

Sample:	**Income**		**Employment and Wages**		**Social Benefits**	
Dependent Variable:	Any Income (1)	Monthly Income (2)	Employed (3)	Monthly Wage (4)	Any Benefits (3)	Monthly Benefits (4)
OLS: Housing Assistance	0.146***	202.2***	0.0834***	134.7***	0.130***	88.36***
All Controls	(0.0109)	(14.36)	(0.00794)	(14.14)	(0.0107)	(9.436)
RF: Housing Placement Rate	0.162***	271.4***	0.152***	269.3***	0.0566	17.40
All Controls	(0.0366)	(89.07)	(0.0447)	(83.19)	(0.0397)	(35.51)
2SLS: Housing Assistance	0.264***	442.5***	0.242***	429.4***	0.0923	28.36
All Controls	(0.0609)	(148.4)	(0.0724)	(135.3)	(0.0646)	(57.83)
Dependent Mean	0.76	586	0.14	196	0.67	399
Complier Dependent Mean if No Housing Assistance	0.49	390	0.05	69	0.44	323
Number of Assessments	23,054	23,054	23,387	23,387	23,054	23,054

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.

Table D.7. The Effect of Housing Assistance on Social Benefits Take Up.

Social Benefit Type:	**General Relief**	**SSI**	**SSDI**	**Food Stamps**
	(1)	(2)	(3)	(4)
OLS: Housing Assistance	0.00257	0.0646***	0.0376***	0.104***
All Controls	(0.00630)	(0.00815)	(0.00584)	(0.0133)
RF: Housing Placement Rate	-0.0178	0.0365	0.0104	0.0180
All Controls	(0.0197)	(0.0310)	(0.0215)	(0.0366)
2SLS: Housing Assistance	-0.0280	0.0582	0.0165	0.0304
All Controls	(0.0313)	(0.0497)	(0.0344)	(0.0617)
Dependent Mean	0.10	0.26	0.09	0.56
Complier Dependent Mean if No Housing Assistance	0.08	0.20	0.09	0.45
Number of Assessments	15,510	23,387	23,387	18,773

Note: All specifications include site x month of assessment FEs and all the controls listed in Table 1. Standard errors are two-way clustered at the case worker and individual level. *p<0.1, **p<0.05, ***p<0.01.