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# The Effect of Housing First Programs on Future Homelessness and Socioeconomic Outcomes*

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**Abstract**

Housing First programs provide housing assistance without preconditions for homeless individuals as a platform for rehabilitation. Despite the programs' increasing popularity, limited evidence exists on their effects on socioeconomic outcomes. Using a novel dataset combining administrative records from multiple public agencies in Los Angeles County and a random case manager assignment design, I estimate that Housing First assistance reduces homelessness and crime, increases income and employment, and does not have a detectable effect on healthcare utilization. Cost-benefit analysis implies that these potential savings offset program costs within 18 months. These findings demonstrate that Housing First can be rehabilitative and cost-effective.

**JEL:** H42, I38, J18
**Keywords:** Homelessness, Housing First, Case managers

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# 1 Introduction

Homelessness is rapidly growing in US cities. There are approximately 580,000 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 (Henry et al., 2020, 2021). Homelessness is associated with multiple adverse outcomes 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).

The Housing First approach to homelessness, which is based on the idea that housing stabilizes a person's life and serves as a platform for rehabilitation, has been the popular treatment approach for homelessness in recent years, with funding for Housing First programs (i.e., rental subsidies combined with supportive services) serving individuals experiencing homelessness more than doubled in the past decade, reaching more than $18 billion nationally in 2019 (United States Interagency Council on Homelessness, 2019; Johnson and Levin, 2018).[1] However, there is mixed evidence regarding the impact of Housing First programs on housing stability and homelessness compared to traditional care, and little evidence about its effect on non-housing outcomes (e.g., crime, employment, health) due to lack of comprehensive longitudinal data on individuals experiencing homelessness, non-random selection of participants into Housing First programs, and challenges in conducting randomized controlled trials (Evans et al., 2019; National Academies of Sciences, Engineering, and Medicine, 2018; O'Flaherty, 2019).

This paper studies the effect of Housing First programs on future homelessness and other socioeconomic outcomes such as crime, employment, and health. A newly constructed comprehensive panel dataset compares outcomes

[1] There are two contested approaches regarding the role of housing assistance as a treatment policy for homelessness. The Housing First approach emphasizes housing as a platform for rehabilitation (Burt et al., 2017). In contrast, the Treatment First approach holds that individuals experiencing homelessness would not be able to maintain housing without first addressing the problems that caused them to be homeless (Katz, 1990; Husock, 2003).

of single adults (i.e., individuals age 25 or older who do not have any dependents accompanying them) experiencing homelessness who receive Housing First assistance to those who do not. This comparison is made possible by linking administrative records across multiple public service agencies in Los Angeles County, including the homeless response system, health services, and the sheriff's department, among others. These links are used to create a panel dataset at the case-month level containing public service histories of all single adults experiencing homelessness who sought assistance from homeless services providers in Los Angeles County between 2016 and 2017.

I address potential non-random assignments into Housing First programs using a random case manager assignment design to construct an instrumental variable for housing assistance receipt. Naive comparison of individuals who receive housing assistance to those who do not could lead to wrong conclusions that result from selection into Housing First programs based on observed and unobserved characteristics of clients. For example, prioritizing individuals with relatively higher acuity into treatment might result in treated individuals having relatively worse outcomes than non-treated individuals. Alternatively, selection into treatment based on unobserved potential gains would lead to estimating excessively large positive treatment effects. I overcome this potential selection problem by exploiting a quasi-experiment where individuals are randomly assigned into Housing First programs with different probabilities based on their case manager assignment. This quasi-experiment results from the as-good-as-random assignment of clients' cases to case managers combined with considerable variation between case managers in their propensity to place individuals in Housing First programs, even after conditioning on service site, time, and case characteristics.

This paper provides three main results. First, Housing First programs reduce future interactions with the homeless support system. I find that a 10-percentage point (approximately one standard deviation) increase in a case manager's Housing First program placement rate increases the probability of Housing First program placement by 8.5 percentage points, and decreases the likelihood of returning to the homeless support system by 1.7 percentage points within 18 months after intake (medium-term) and by 1.2 percentage points within 30 months after intake (long-term), relative to sample means of 27 and 22 percent, respectively. Rescaling these effects by the first-stage (treatment assignment propensities) magnifies the estimates such that participation in Housing First programs lowers the probability of returning to the homeless support system within 18 months by 23 percentage points and within 30 months by 15 percentage points.

Second, Housing First programs positively affect a wide range of non-housing outcomes. Using the instrument of case manager Housing First program placement propensity, I estimate that participation in a Housing First program reduces crime and reliance on social benefits and increases income and employment. Specifically, Housing First assistance reduces the probability of being in jail within 18 months by 95 percent, the probability of having a criminal charge by 85 percent, the probability of receiving emergency cash assistance by 80 percent, and the probability of relying on social benefits by 35 percent, while increasing the probability of reporting non-zero income by 23 percent (compared to baseline means). Importantly, these effects are also detected 30 months after intake. Additionally, I find no significant relationship between Housing First assistance and health services utilization, which is consistent with the previous literature (National Academies of Sciences, Engineering, and Medicine, 2018).

Third, I provide descriptive evidence that both short-term (rapid re-housing) and long-term (permanent supportive housing) Housing First programs generate positive effects for recipients. The estimated effects on the wide range of socioeconomic outcomes considered in this paper are similar in sign for both types of programs. As expected, long-term Housing First programs produce considerably larger effects in magnitude in future homelessness compared to short-term Housing First programs. Nevertheless, the estimates suggest that short-term Housing First programs deliver much more favorable outcomes in crime, health, income, and employment, and that they also deliver these outcomes faster. These results are more descriptive in nature compared to the previous two, since the random assignment in this study is for *any* Housing

First program and not for the *type* of Housing First program.

Overall, these findings have important implications for policy debates over eligibility, duration, and targeting of Housing First assistance to individuals experiencing homelessness. One important policy question is whether the positive effects of housing are cost-effective. Back-of-the-envelope calculations presented at the end of the paper show that program costs are offset by direct savings to public agencies within the first 18 months alone, which I compute as savings from reduced use of public services and increased employment.

This paper advances the literature by adding to the growing trend of using administrative data to study homelessness, which was pioneered by Culhane et al. (2002) and Byrne et al. (2013), with recent work demonstrating the use of administrative data to study homelessness at the national level (Meyer et al., 2021). Furthermore, this study establishes that participation in Housing First programs has a beneficial causal effect on a wide range of socioeconomic outcomes for individuals experiencing homelessness using large-scale administrative data and the random assignment of screener design.[2] Recent literature reviews by Evans et al. (2019), O'Flaherty (2019), and Kertesz and Johnson (2017) show that there is mixed evidence in the literature regarding the effects of Housing First programs on future homelessness and housing stability, especially for rapid re-housing (short-term) programs. In addition, few papers have been able to detect significant effects of Housing First policies on non-housing 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 from multiple public agencies on a large population of individuals experiencing homelessness.

This study also contributes to the literature on homelessness by focusing on

[2]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 many different contexts, including incarceration (Aizer and Doyle, 2015; Bhuller et al., 2020; Kling, 2006; Mueller-Smith, 2015), 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).

single adults experiencing homelessness, an understudied yet substantial population representing more than two-thirds of the homeless population. Much of the existing literature focuses on homeless families or specific subgroups within the homeless population. For example, the closest study to this one is Gubits et al. (2018) which evaluates the effects of the Family Options study. The study randomly assigned families experiencing homelessness to priority access to long-term rent subsidies, short-term rent subsidies, transitional housing programs, and usual care. They find that long-term rent subsidies reduced homelessness and improved aspects of well-being relative to usual care, while the two other interventions had little effect. The differences in the effectiveness of short-term rental subsidies (e.g., rapid re-housing) programs in the Family Options study and this paper emphasize the heterogeneous impacts of housing programs on families relative to single adults experiencing homelessness. Other seminal studies include Goodman et al. (2016) who study the Homebase homelessness prevention program in New York City, Rosenheck et al. (2003) that study the effect of rent subsidies for homeless veterans with serious mental illness, and Tsemberis et al. (2004) who study the effect of Pathways to Housing program in New York City that was targeted to individuals with serious mental illness.

Last, this paper also relates to the growing literature in economics on the effect of housing policies on family and individual outcomes by examining the impact of housing assistance for individuals experiencing homelessness. This literature has mainly focused on specific populations such as people who apply for housing vouchers, like in the Moving to Opportunity studies (Bergman et al., 2019; Chetty et al., 2016; Kling et al., 2007; Pinto, 2018), or who are forced to move after public housing demolitions, like Jacob (2004) and Chyn (2018). Other studies, like Jacob and Ludwig (2012) and van Dijk (2019), study broader populations of low-income families. What is common to these studies is that they cannot identify homeless participants due to the lack of available data on participants. In addition, a few studies have examined the effect of housing evictions on homelessness, finding that they cause a large and persistent increase in the risk of homelessness (Collinson and Reed, 2018;

Desmond and Gershenson, 2016; Fetzer et al., 2019; Humphries et al., 2019).[3] This study, however, evaluates what is the effect of housing assistance for individuals who are already experiencing homelessness.

# 2 Background

This section summarizes the housing programs available for individuals experiencing homelessness and provides a brief description of Los Angeles County's homeless support system. For more details, see Appendix A.

## 2.1 Housing First Programs for Homeless Individuals

There are two broad categories of housing programs that serve the homeless population: temporary (emergency) and permanent (Housing First). Temporary housing programs provide short-term housing solutions for clients while they experience homelessness.[4] In contrast, permanent housing programs exit individuals from homelessness by offering medium- or long-term rent subsidies combined with supportive services.[5]

There are three main permanent housing programs: rapid re-housing, permanent supportive housing, and other permanent housing. Rapid re-housing

[3]See Ellen et al. (2016) for an overview of empirical research on housing assistance policies in the U.S.

[4]Temporary (emergency) housing programs are based on the traditional continuum model for homelessness. This model is based on the idea that individuals who experience homelessness face many challenges that must be addressed first in order to achieve future housing stability. The first access point for individuals experiencing homelessness under this model is emergency shelters. They provide crisis or bridge housing without rent or lease agreements until residents can find permanent housing. After accessing an emergency shelter, individuals can move to a transitional housing program. Like emergency shelters, transitional housing programs provide temporary assistance for up to 24 months. In addition to providing shelter, temporary housing programs provide supportive services that address housing placement, self-sufficiency, employment and training, life skills, mental and physical health, and substance abuse.

[5]Permanent housing programs are based on the Housing First strategy for addressing homelessness. This strategy is based on quickly finding long-term housing solutions without preconditions or eligibility requirements in order to minimize the trauma caused by homelessness and to serve better additional problems an individual experiencing homelessness is facing (Burt et al., 2017).

programs locate housing units for clients in the private market. They typically offer short-term total rent subsidies lasting up to 18 months. In addition to housing search and rent subsidy, these programs also offer non-housing services such as case management, supportive services, and other limited short-term financial assistance.

Permanent supportive housing and other permanent housing programs (e.g., project-based Section 8 or Housing Choice Vouchers for individuals experiencing homelessness) offer long-term rental subsidies that pay the difference between 30 percent of individuals' incomes and their housing costs. Program participation can be indefinite as long as individuals remain eligible and follow program rules such as paying their share of the rent. Those subsidies can be place-based (project-based) or tenant-based that allow recipients to rent private market housing. Permanent supportive housing programs, which serve persons with disabilities, also provide intensive non-housing services such as case management, substance abuse treatments, mental health treatments, life skills courses, and employment readiness workshops.

## 2.2 Los Angeles County's Homeless Support System and Case Manager Assignment

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 operate in a decentralized fashion. These organizations widely differ in the populations they serve and in the scope and type of services they provide, ranging from meals and hygiene services, health care, transportation, legal assistance, general case management, and temporary or permanent housing services.

Single adults experiencing homelessness 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 receive referrals to service providers via other public agencies (e.g., health clinics, hospitals, jails). 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 managers who conduct an intake using a standardized tool known as the VI-SPDAT (Vulnerability Index - Service Prioritization Decision Assistance Tool). After completing the intake, case managers provide case management services for their clients, resulting in an "action plan" or treatment recommendation. As part of this plan, clients can receive housing and non-housing services from different service providers, according to their needs and availability.

Two features of the Los Angeles County homeless support system are essential for the analysis in this paper. First, when a client engages with a service provider in the system, they are assigned the first available case manager, so conditional on the service provider and time, the assignment to a case manager is as-good-as-random.[6] Second, case managers differ in their propensity to place individuals in Housing First programs. The quasi-experiment the results from these two features generates exogenous variation in the likelihood of receiving Housing First assistance based on case manager assignment.

At this point, it might be helpful to discuss why case managers might arrive at different action plans and outcomes for similar clients. If program eligibility and suitability were always clear and based on a clear-cut rule, there should be no variation across case managers with randomly assigned cases. There is extensive literature on case manager variation in recommendations and outcomes (Sosin and Yamaguchi, 1995; Alden, 2015; van den Berk-Clark, 2016), which provides some support for the identification strategy employed here. In particular, case managers are thought to rely more heavily on "practice wisdom" than administrative rules when making placement referrals.[7] In ad-

[6] The random assignment of clients to case managers has been confirmed in multiple interviews conducted with service providers and with representatives from the Los Angeles Homeless Services Authority (LAHSA). They have emphasized that this assignment is based on the availability of case managers alone. This is true for all types of initial engagement of clients with providers (walk-ins, referrals, and outreach). Section 4.4 provides empirical evidence that case managers' assignments are as-good-as-random.

[7] Multiple interviews with homeless service providers in Los Angeles County emphasized that several case managers' unobserved personality traits and skills might be important

dition, the likelihood for placement in Housing First programs does vary over time and with the number of resources available to each organization, such as federal and local funding and private donations (Moulton, 2013; Corinth, 2017; Lucas, 2017). Hence, it appears that the threshold for placement is not constant across time or case managers.

# 3 Data

A unique dataset that combines a wide array of administrative agencies in Los Angeles County is used to carry out the analysis. This section describes these data sources and the structure of the linked dataset. It then provides descriptive statistics and reports correlations between housing assistance and medium- and long-term outcomes as a benchmark to interpret the magnitude of the causal effects of case managers and housing. Detailed information on the different agencies included in the analysis, the available data, and the cleaning and setting up of the data for the analysis is available in Appendix B.

## 3.1 Homeless Support System Data

The core of the data comes from the Los Angeles Homeless Services Authority (LAHSA). The VI-SPDAT database offers details of intakes conducted by homeless service providers throughout Los Angeles County for single adults experiencing homelessness in 2016-2017. Each record includes a unique individual identifier, intake date, survey questions, and demographic characteristics. Additionally, each record provides information on the case manager conducting the intake, including their name, organizational affiliation, and intake location.[8]

determinants of housing placement rates. Firs, case managers are required to build trust and motivate their clients, and serve as their clients' point of contact and advocates. The second important characteristic of case managers is finding 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.

[8]A VI-SPDAT survey is a pre-screening tool that guides case managers to determine the level of acuity of a particular client, which in the case of single adults ranges from a score of

The Homeless Management Information System (HMIS) contains complete records of all publicly funded homeless services provided (both housing and non-housing services) by homeless service providers in Los Angeles County. The VI-SPDAT and the HMIS databases are linked to determine whether individuals were ever enrolled in a Housing First program. The two databases reflect that, in many cases, once an individual is placed in a housing program, a separate organization or agency supervises the case.

The baseline treatment used in this study is enrollment in any Housing First program that provides rental subsidy (i.e., rapid re-rehousing, permanent supportive housing, or other permanent housing programs) at any point during the first 6-months after intake.[9] This measure excludes any continuum programs (i.e., emergency shelters and transitional housing).[10]

The main outcome measures using this data are defined as use of homeless programs at any point after intake.[11] These programs include emergency shelter stays, street outreach, new case intakes, and continued enrollment in Housing First programs. These outcomes have been traditionally used as measures of homelessness and housing stability (Evans et al., 2016; Gubits et al., 2018; Weare, 2021).[12]

Lastly, the Homeless Management Information System (HMIS) also contains self-reported income, employment, and social benefits receipt. This paper uses these responses to examine the effects of Housing First programs on

0 to 17. Higher levels of the VI-SPDAT score indicate a higher level of acuity and, hence, a higher need for assistance. In practice, there is very little correlation between an intake's VI-SPDAT score and the likelihood of receiving housing assistance.

[9] Treatment is censored at 6-months from intake date to balance two opposing empirical challenges: long waiting times for Housing First programs and lack of indication in the data regarding whether a housing placement is linked directly to the case manager handling the individual during intake. Censoring the treatment at 1-month, 3-months, 12-months, and 18-months after intake does not materially change results.

[10] I exclude continuum programs from the analysis for two reasons. First, individuals in continuum programs are considered homeless since they do not have a permanent housing solution. Second, one of the main challenges in the homelessness literature is to investigate the impact of Housing First programs on individuals' outcomes and to compare them to those of traditional continuum programs (Burt et al., 2001; Kertesz and Johnson, 2017).

[11] The outcomes in this paper will focus on any program use between 7-18 (medium-term) and 19-30 (long-term) months after intake.

[12] See Appendix B for a more detailed description of these outcome measures.

outcomes derived from these responses. However, two main caveats require caution when interpreting results related to these outcomes. First, this data is self-reported, as opposed to other outcomes in the study that rely on administrative records. Second, this data is available only for individuals who provide information on employment, income, or social benefits receipt.[13]

### 3.2 Public Agencies Data

The Enterprise Linkages Project (ELP) includes information across a spectrum of publicly funded health, mental health, social and corrections services in Los Angeles County. I summarize the key outcome measures relevant for the analysis based on three major areas: crime, health, and social benefits.

*Crime.*– The analysis uses two data sources to measure crime-related outcomes. First, the Los Angeles Sheriff's Department (LASD) records contain information on the population of charged and incarcerated individuals in Los Angeles County. The dates of each unique sentence are observed, the type of charge, and the total sentence length. Specifically, the data contain criminal charges, arrests (jail bookings), and incarceration history.[14] Second, the Los Angeles County Probation Department records contain information on the population of offenders that are under probation supervision in Los Angeles County in a given month.

*Health.*– Three data sources are used to measure health-related outcomes. First, the Los Angeles County Department of Health Services (DHS) database contains payment records for medical services funded by Los Angeles County. The variables include the type of service (inpatient, outpatient, emergency department), start and end dates of services, and diagnosis and procedure

[13]Another caveat related to these results is that when measuring outcomes at 7-18 months after intake (medium-term) or 19-30 months after intake (long-term), the individual must have an interaction with the homeless support system (enrollment in a housing program or return to homelessness). Reassuringly, the main results in the paper are similar for this subgroup of individuals, and they are available upon request.

[14]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.

codes. Second, the Los Angeles County Department of Mental Health (DMH) records contain publicly funded mental health services, including assessments, case management, crisis intervention, medication support, peer support, psychotherapy, and rehabilitative services. Third, the Los Angeles County Department of Public Health (DPH) database records information on substance-abuse services, including detox, residential programs, and outpatient visits.

*Social Benefits (General Relief).–* General Relief is an emergency cash assistance program operated through the Los Angeles County Department of Public and Social Services (DPSS). Eligible for General Relief is those individuals who are unable to work and are not eligible for other state or federal cash assistance programs. Hence, the vast majority of individuals receiving this benefit are homeless. The General Relief records contain the monthly benefits each member of a household receives.

### 3.3 Sample Restrictions

Starting from the raw dataset of intakes, I make a series of restrictions to obtain the baseline sample of 15,353 intakes. The cases in the baseline sample are of non-veterans single adults for which this is their first interaction with the homeless system in Los Angeles County.[15] In addition, I restrict attention to service sites that had at least two case managers working each month and case managers who handled at least 30 cases in 2016-2017, so that case manager randomization is meaningful.[16] Appendix B describes the steps above in more detail, and Table C.1 shows how the various restrictions affect the number of cases, clients, case managers and service sites.

[15] I remove veteran cases because homeless veterans are redirected to the United States Veterans Administration Homeless System for further treatment. Hence, their case manager assignment is not relevant to whether they receive housing .

[16] In Section 5.4, I show that my results are robust when excluding case managers with a relatively small number of cases. I chose the threshold of 30 cases to increase the sample size. Case managers handle 30 cases on average at any point in time, with the average duration of a case more than one year, making 30 cases a reasonable number in this setting.

### 3.4 Summary Statistics

Table 1 reports summary statistics for the baseline sample of 15,353 cases described above. The typical case in the analysis represents an individual with an average age of 45 years old, less likely to be female, more likely to be from a minority group and to experience homelessness in the past. Moreover, 4 out of 5 cases report having a major disability, a quarter of cases report having a substance abuse problem, and almost two thirds are considered chronic homeless. In addition, between 18-25 percent of cases had past interactions with at least one public agency.

Panel C of Table 1 presents a summary of homeless services received for the homeless cases in the sample. Homeless service is defined as enrollment in any housing or non-housing program up to six months after intake. For simplicity, I consider the first program in which the individual enrolled after intake as the mutually exclusive treatment assigned to that individual. Among the 15,353 cases in the analysis, 7 percent of cases received Housing First assistance (rental subsidy), and less than 1 percent of all cases received long-term rental subsidies, the most intensive housing assistance program available.[17]

Panel D of Table 1 presents a summary of the outcomes.[18] It shows that about a quarter of individuals return to seek assistance from the homeless support system at least once in both the medium- and long-terms. Turning to non-housing outcomes, the table shows that, in the medium-term, 9 percent of cases report receiving emergency cash assistance (general relief) at least once, 7 percent of cases visited a DHS facility, only 1-2 percent received mental

[17] Figure C.1 presents the CDF of duration of Housing First assistance (figure a) and the CDF of waiting time to Housing First assistance (figure b). The median duration of housing assistance is 320 days and the median waiting time is 15 days. In addition, approximately 45 and 32 percent of treated cases are still actively enrolled in a housing program 18-months and 30-months after intake, respectively.

[18] The availability of data on outcomes naturally varies across intake dates and agencies due to data censoring. I observe returns to the homeless system for all 15,353 cases in the medium-term (7-18 months after intake) and only for 8,947 cases in the long-term (19-30 months after intake). When considering the other public agencies in the analysis, I observe between 9,771 (DPSS sample) and 4,376 (DPH sample) cases in the medium term. I can only observe outcomes for shorter time periods for some agencies and relatively small samples in the long term.

health or substance abuse services, and 6 percent of cases had at least one jail booking, Finally, the last three rows of Panel D show that among individuals reporting income information, 80 percent had non-zero income, 70 percent reported receiving social benefits, while only 14 percent reported employment.

Table C.2 reports coefficients from OLS regressions of various medium- and long-term individual outcomes on Housing First program treatment. Housing First assistance receipt is negatively correlated with measures of homelessness, positively correlated with a measure of housing stability, and not correlated with most health and crime outcomes, regardless of whether controls and fixed effects are included in the regressions.

The cross-sectional correlations presented in Table C.2 must be taken with caution. Using an OLS regression to estimate the causal effect of housing assistance on socioeconomic outcomes can lead to wrong conclusions because the group of individuals who receive housing assistance is not necessarily comparable to those who do not, in both their observed and unobserved characteristics. A significant concern is the non-random selection of individuals to Housing First programs based on the observed and unobserved likelihood of having positive gains from treatment. These concerns motivate the use of an instrumental variable design to address unobserved selection to treatment.

## 4 Research Design

I exploit the fact that assignment of homeless cases to case managers is as-good-as-random and that case managers differ in their propensity to place clients in Housing First programs to generate exogenous variation in the probability of receiving housing assistance. This reduced-from relationship identifies the causal effect of case manager assignment on future homelessness and a large set of socioeconomic outcomes. Additionally, I leverage this variation using a leniency design, which aims to identify the causal effect of Housing First programs on the same set outcomes.

### 4.1 IV Model

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

The main interest of the analysis is in the causal effect of Housing First programs on subsequent homelessness and a wide array of socioeconomic 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 $\beta_t$ is the parameter of interest, $H_i$ is an indicator variable equal to 1 if individual $i$ enrolled in Housing First program in the six months after intake, $\delta_{sm}$ is a set of fully interacted service site by month of intake fixed effects, the level at which random assignment to case managers 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 intake (e.g., the number of returns to the homeless support system within $t$ months from intake).[19]

The case manager assignment design addresses endogeneity and selection concerns by exploiting the quasi-random assignment of cases to case managers (conditional on service site and month of intake) and the fact that some case managers are systematically more likely to place individuals in Housing First programs. Taken together, this leads to quasi-random variation in the probability an individual will enroll in a Housing First program depending on which case manager they are assigned to. The analysis uses this exogenous variation

[19] The complete list of individual-level controls includes the following variables: age (in years), age-squared, female indicator, race indicators (Black, Hispanic, non-Hispanic white, other/multiple/missing races), homeless history indicator, disability indicator, substance abuse indicator, chronic homeless indicator, health emergency in past six months indicator, any jail booking in past six months indicator, public agencies' history (any record in the past five years for DHS, DMH, DPH, Sheriff, Probation, and General Relief), and any past housing assistance not related to homelessness indicator.

in $H_i$ to draw inference about the causal effect of the Housing First programs for individuals experiencing homelessness.

The main analysis is based on 2SLS estimation of $\beta_t$ 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 First program placement rate of case manager $j$ assigned to individual $i$'s case. Formally, it is defined as:

$$Z_{j(i)} = \frac{\sum_{k \neq i} H_{jk}}{N_j - 1} \tag{3}$$

where $H_{jk}$ equals to 1 if individual $k$ who was assigned to case manager $j$ enrolled in a Housing First program, and 0 otherwise, and $N_j$ is the number of intakes conducted by case manager $j$ in 2016-2017. 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 First assistance among the subgroup of individuals who could have received a different treatment had their case been assigned to a different case manager.

### 4.2 First Stage

Figure 1 shows the identifying variation in the data by providing a graphical representation of the first stage. The histogram in the background of the figure shows the distribution of the instrument (controlling for fully interacted service site by month of intake fixed effects and individual-level covariates). The mean of the instrument is 0.07, with a standard deviation of 0.07. The histogram reveals variation in a case manager's tendency to place individuals in Housing First programs. For example, a case manager at the 90th percentile places about 10 percent of cases in Housing First programs compared to approximately 3 percent for a case manager at the 10th percentile.

Figure 1 also plots the probability that clients enroll in a Housing First program as a function of their assigned case manager Housing First program 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 enrolling in a Housing First program is monotonically increasing in the case manager's placement rate and is close to linear.

Table 2 reports first stage estimates where the dependent variable is a dummy for whether an individual received Housing First assistance in the current case on the case manager's Housing First placement rate. Column 4 includes fully interacted service site by month of intake fixed effects and a large set of case-level characteristics. The estimate is highly significant, suggesting that being assigned to a case manager with a 10-percentage point (approximately one standard deviation) higher Housing First placement rate increases the probability of Housing First program enrollment by 8.5 percentage points.

There is no statistically significant relationship between observable case manager characteristics and their Housing First placement rates. First, there is no statistically significant difference in placement rates based on the implied gender or ethnicity of the case manager. Second, the variation in case managers' placement rates is not explained by tenure or experience (See Figure C.2). Bearing in mind that there could be many reasons why some case managers are more likely to place clients in Housing First programs than others, as long as case managers' assignment to clients is random, these underlying reasons should not matter for the causal interpretation of this analysis.

### 4.3 Reduced Form

This section presents the reduced form relationships between case manager assignment and future homelessness, crime, health, and economic outcomes. Given that there is conditional random assignment of cases to case managers, these relationships can be interpreted as the causal effect of being assigned to a case manager with a higher Housing First placement rate.[20]

Panels (a)-(f) of Figure 2 plot the reduced-form relationships between a case manager's Housing First placement rate and the following outcomes, us-

[20]Section 4.4 provides quantitative evidence for conditional random assignment of cases to case managers.

ing local linear regression (by order of appearance): any return to the homeless support system, number of jail bookings, number of emergency department visits, number of mental health treatments, any non-zero income reported, and any employment reported. All outcomes are measured between 7-18 months after intake and are supposed to capture the medium-term effect of case manager assignment.[21]

The reduced-form estimates relate to the case manager Housing First program placement rate in a monotonic fashion, with varying precision. First, the likelihood of returning to the homeless system at least once in the medium-term (between 7-18-months after intake) is monotonically decreasing in the case manager placement rate (panel (a)). Approximately 27 percent of individuals with cases assigned to a case manager with a low placement rate (placement rate = 0.03, 10th percentile) are expected to return at least once to seek assistance from the homeless system, contrasted with approximately 25 percent of individuals whose cases are assigned to a case manager with a relatively high placement rate (placement rate = 0.1, 90th percentile).

Second, the number of jail bookings (panel (b)) is monotonically decreasing with the case manager placement rate. For example, the difference between the 10th and 90th percentile of case manager housing in the number of jail bookings in the 18 months after intake is around 0.3 fewer jail bookings for those individuals whose cases are assigned to case managers with a higher placement rate, relative to a baseline mean of 0.6 jail bookings.

Third, the number of emergency department visits is non-increasing with the case manager's placement rates (panel (c)). This relationship suggests modest to no effects of case manager's placement rate on utilization of public emergency health services, although these are not precisely estimated. However, panel (d) shows that the number of public mental health treatments received monotonically increases with the case manager's placement rate. The hypothesized effect of case manager placement on this outcome is ambiguous since increased mental health services do not necessarily imply a deterioration

[21]The first six months are excluded when measuring the outcomes to ensure treatment starts before outcomes are realized.

in one's mental health.

Finally, the likelihoods of reporting non-zero income (panel (e)) and employment (panel (f)) are both monotonically increasing with the case manager placement rate. The difference between the 10th and 90th percentile of case manager placement rates in the probability of reporting employment is around four percentage points higher for those individuals whose cases are assigned to case managers with a higher placement rate.

### 4.4 Instrument Validity

For the instrument to be valid and interpreted as a local average treatment effect, it needs to satisfy the exogeneity, monotonicity, and exclusion assumptions, in addition to the relevance (first stage) assumption. In this subsection, I test for the exogeneity and monotonicity assumptions. I discuss the exclusion assumption in depth in section Section 5.5

#### Instrument Exogeneity

Table 3 presents evidence that case manager assignment is as-good-as-random. Columns 1-2 show results from a regression of the case manager Housing First program placement rate on a variety of individual-level covariates measured before intake, conditional a set of fully interacted service site by month of intake fixed effects. 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 manager's placement rate and the various individual-level covariates, either individually or jointly.[22]

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 regressions. If case managers are randomly assigned, pre-determined variables

[22] The indicator variable for Black is the only statistically significant coefficient at the 10 percent significance level. However, the size of this coefficient is less than 10 percent compared to the mean case manager placement rate, implying that the economic significance of this variable on case manager placement rate is negligible.

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 public agencies are included.

**Monotonicity**

If the causal effect of Housing First 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 this setting, the monotonicity assumption requires that individuals assigned to a case manager with a low placement rate and received Housing First assistance would also receive Housing First assistance if assigned to a case manager with a high placement rate. This assumption ensures that the 2SLS estimand can be given a local average treatment effect interpretation.

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 columns 1 and 3 of Table C.3. Panels A-E split the sample by chronic homeless status, age, gender, race, and ethnicity. The first stage estimates are positive and statistically different from zero for all these subsamples, consistent with the monotonicity assumption.

A second implication of monotonicity is that case managers should have a high Housing First program placement rate for a specific case (e.g., chronic homeless) if they have a high placement rate in other case types (e.g., not chronic homeless). 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 manager's Housing First program placement rate for cases outside of the subsample. For example, for the chronic homeless subsample, I use a case manager's Housing First program placement rate constructed from all cases except chronic homeless cases. Columns 2 and 4 of Table C.3 list 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 managers who have a high Housing First program placement rate for one type of case also have a high placement rate for other cases.

# 5 Results

I provide evidence that Housing First program placement prevents and reduces future returns to the homeless support system, jail bookings, criminal charges, and emergency cash assistance receipt. However, I do not find any detectable relationship between Housing First program placement and health services utilization. Additionally, I show that Housing First program placement increases income and employment reports. Following that, I explore the potential channels through which Housing First programs affect individuals, including treatment versus post-treatment effects, extensive versus intensive margin responses, and duration of assistance. Last, I document heterogeneous effects by individual and program characteristics.

## 5.1 Main Results

### Homelessness and Housing Stability

Panels A and B of Table 4 present reduced-form (RF) and instrumental variable (IV) estimates of the effect of case manager assignment and Housing First program placement on various outcomes related to homelessness and housing stability. The outcome in column 1 measures any return to the homeless support system between 7-18 months after intake (panel A) and 19-30 months after intake (panel B).[23] Case manager assignment and Housing First program placement significantly reduce the probability of returning to the homeless system, both in the medium- and long term. In particular, being assigned to a case manager with ten percentage points higher placement rate decreases the likelihood of returning to the homeless system by 1.7 percentage points in the

[23] Return to the homeless system is defined as either staying at an emergency shelter, receiving services from a street outreach program, or applying for homelessness assistance again by having a new case and intake managed by a different case manager.

medium-term and 1.2 percentage points in the long-term, compared to baseline means of 27 and 22 percent, respectively. The IV estimates suggest that the likelihood of returning to the system for individuals who receive housing assistance reduces by 20 percentage points in the medium-term and 15 percentage points in the long-term, which is equivalent to a 75 and a 68 percent reduction in future homelessness.[24]

Panels (a) and (b) of Figure 3 graphically present IV estimates of the effect of Housing First assistance receipt on the probability of returning to the homeless support system for the medium-term and long-term samples. The graphs present a series of cumulative monthly estimates from 7 months to 18 or 30 months after intake. For example, the estimate at month 12 uses the probability that an individual has returned to seek services from the homeless support system at least once from month 7 to month 12 after intake 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 intake increases. The estimates suggest that there is a large and statistically significant reduction of approximately 20 (30) percentage points in future homelessness for those receiving Housing First assistance at 18 (30) months after intake.

Columns 2-4 in the top part of Table 4 decompose the return to the homeless system outcome into its three components: emergency shelter stays, street outreach, and new intakes. Both the reduced-form and IV estimates of these outcomes are similar in sign, magnitude, and statistical significance, suggesting that no one component of the return to homeless system measure is driving

[24]It is important to emphasize that the data used in the analysis does not observe whether an individual is homeless at any given point in time, only whether the individual has returned to the homeless system. The future homelessness measure addresses this measurement issue by including new enrollments in street outreach programs in addition to shelter stays and new intakes. Street outreach workers actively seek homeless individuals on the streets, implying that the homelessness 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 experience homelessness. The analysis implicitly assumes that case manager assignment is not correlated with these possibilities.

the results. Column 5 in the top part of Table 4 measures any enrollment in a Housing First program. It is a measure of housing stability as it indicates whether individuals are maintaining program eligibility and continue to be housed. The estimates, which are large in magnitude and significance, suggest that case manager assignment is highly predictive of future enrollments in housing programs and that enrolling in a Housing First program in the first six months after intake positively impacts continued enrollment over time.

Finally, column 6 of the top part of Table 4 looks at general relief emergency cash assistance receipt, which is another proxy for homelessness that can. This measure is valuable since it is based on DPSS records rather than the homeless support system, so it can also include individuals who do not seek assistance from the homeless support system. Reassuringly, the estimates from Table 4 suggest that case manager assignment and Housing First assistance significantly reduce the likelihood of receiving general relief.

### Crime

Columns 1-3 in panels C and D of Table 4 present estimates of the effect of case manager assignment and Housing First assistance on various outcomes related to crime. The dependent variable in column 1 measures any jail booking by Los Angeles County's Sheriff Department between 7-18 months after intake (panel C) and 19-30 months after intake (panel D). Case manager assignment and Housing First assistance significantly reduce the probability of a future jail booking, both in the medium- and long-term. In particular, being assigned to a case manager with a ten percentage points higher placement rate decreases the likelihood of a future jail booking by 0.5 percentage points in the medium-term and one percentage point in the long-term, compared to baseline means of 6 and 5 percent, respectively. The IV estimates suggest that the effect is much more significant for individuals who receive Housing First assistance. For these individuals, the likelihood of a future jail booking is reduced by six percentage points in the medium-term and 13 percentage points in the long-term.[25]

Panels (c) and (d) of Figure 3 graphically present IV estimates of the effect of Housing First assistance receipt on the probability of a future jail booking for the medium-term and long-term samples, respectively. All of the IV estimates are negative and statistically significant. The estimates become larger in magnitude over time and reaches more than 20 percentage points reduction in jail bookings 30 months after intake.

Columns 2 and 3 in the bottom part of of Table 4 look at two additional crime-related outcomes: any criminal charge and any probation case. Like jail bookings, case manager assignments and Housing First assistance receipt have a negative effect on the likelihood of having any criminal charge. Finally, I do not find any significant relationship between case manager assignment or Housing First assistance receipt on the likelihood of being under probation. The medium-term estimates for being under probation are materially zero, and the long-term estimates are negative but statistically insignificant.

### Health

Columns 4-6 in panels C and D of Table 4 present estimates of the effect of case manager assignment and Housing First assistance on various health-related outcomes. The dependent variable in column 4 measures any Department of Health Services (DHS) services receipt between 7-18 months after intake (panel C) and 19-27 months after intake (panel D).[26] Case manager assignment and Housing First assistance have a weak negative effect on future DHS service receipts, both for the medium- and long-term samples. The estimate in the medium term is close to zero. In contrast, the long-term estimate suggests

[25] The IV estimates suggest a 100 percent reduction in incarceration probability in the medium-term and more than 200 percent in the long-term. Palmer et al. (2019) find that emergency financial assistance receipt for families that are on the brink of homelessness reduces violent crime arrests by 51 percent. Rose et al. (2019) finds that being assigned to a teacher with a high value-added lead to both short- and long-run reduction in crime rates. However, Jacob et al. (2014), and Lens (2014) find that housing vouchers have little or no effect at all on children or community crime rates, respectively.

[26] These services include emergency department visits, inpatient stays, and outpatient visits.

a 12 percentage point reduction in the likelihood of receiving a DHS service, although it is only marginally significant.[27]

Moreover, panels (e) and (f) of Figure 3 graphically present IV estimates of the effect of Housing First assistance receipt on the probability of receiving a DHS service for the medium-term and long-term samples. While most of the IV estimates are negative, they are also statistically insignificant. As a result, the impact of case manager assignment and Housing First assistance on health services utilization is inconclusive, with some suggestive evidence that they lead to a reduction in these services, especially over the long run.

Columns 5 and 6 at the bottom part of Table 4 look at two additional health-related outcomes: any department of mental health (DMH) and any department of public health (DPH) treatment. The DMH long-term outcome is measured at 19-30 months after intake, while the DPH long-term outcome is measured 19-23 months after intake. I find little effect of case manager assignment and Housing First assistance on service receipt from these agencies.

### Employment, Income, and Social Benefits

Table 5 presents estimates of the effect of case manager assignment and Housing First assistance on various outcomes related to income, employment, and social benefits. As explained in Section 3.1, these results should be taken with caution due to self-reporting and potential selection concerns.[28] 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 IV estimates show that there is a 17-percentage point increase in the probability of reporting non-zero income and a $715 increase in mean monthly income reported in the 18 months after intake for individuals who received Housing First assistance, with a 42 percentage-point and $640 increase in the 30 months after intake. In columns 3-4, I find similar results for reporting employment and mean monthly wages. Finally, columns 5-6 show

[27]The results are similar when outpatient visits are excluded, and are available upon request from the author.

[28]Reassuringly, the outcomes described earlier continue to hold for the subsample who reports information on income, employment, and social benefits.

that Housing First assistance reduces social benefits receipt in the medium-term and has a positive yet statically insignificant effect on it in the long-term. Taken together, the results in Table 5 suggest that Housing First assistance leads to increased income and that this increase is driven by employment.[29]

### 5.2 Potential Mechanisms

#### Extensive (Prevention) versus Intensive (Mitigation) Margin

A comparison of the medium-term and the long-term outcomes suggests that Housing First assistance not only prevents an individual from returning to the homeless support system, the jail system, the emergency departments, and the hospitals (the extensive margin), but it also prevents individuals from interacting multiple times with these agencies. To further explore the intensive (mitigation) margin response, Figure C.3 plots IV estimates for the cumulative number of returns to the homeless support system (panels (a) and (b)), the cumulative number of jail bookings and criminal charges (panels (c) and (d)), and the cumulative number of DHS services received (panels (e) and (f)) in the months after intake for the medium-term and long-term samples. All estimates are consistent with the previous findings, suggesting that Housing First has both extensive (prevention) and intensive (mitigation) margin effects on utilization of public services that become larger over time.

#### Treatment versus Post-Treatment Effect

The results in Table 4 and Figure 3 can be decomposed into two potential channels: treatment and post-treatment. The treatment channel attributes the observed effects to actively receiving treatment. That is, being enrolled in a Housing First program has a quasi-mechanical effect on the likelihood of

[29] One concern is that preexisting employment and income might be influencing Housing First assistance receipt and other results I find in this section. To explore this probability, I have attempted a version of the baseline model that treats all future outcomes related to health, crime, employment, income, and social benefits, as controls in a specification where the dependent variable is future 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 First assistance channel and not other channels.

returning to the homeless system.[30] On the other hand, the post-treatment channel attributes the observed effects to differences between treated and untreated individuals after treatment has concluded.

Figure C.4 shows a plot of a series of IV estimates for the probability of being enrolled in a Housing First program, 1 to 30 months after intake.[31] It shows that the probability of receiving Housing First assistance for those who received housing assistance within six months after intake starts high and falls over time. The main takeaway from Figure C.4 is that the treatment channel effect goes down over time as fewer treated individuals are actively receiving treatment. In Table C.4, I present biannual estimates for any return to the homeless support system, any jail booking, and any DHS service in a particular six months period. The table reveals sizable reductions in future homelessness and jail bookings across all periods considered and negative but insignificant reductions in DHS services receipt. This is consistent with the idea that the estimated effects are not driven solely by the treatment channel and that the post-treatment channel is also important.[32]

### Duration of Housing Assistance

I explore the role of case managers in the duration of housing assistance.[33] Panel (a) of Figure C.5 graphs housing assistance duration in days (including zeros) as a function of the case manager Housing First placement rate. The upward slope indicates that being assigned to a case manager with a higher

[30] I call this a quasi-mechanical effect because 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 fact, recent studies show that a significant share of participants in homeless housing programs return to homelessness while or after receiving housing assistance (Levitt et al., 2013; Cusack and Ann Montgomery, 2017).

[31] The figure is similar to a survival function, in that if all treated individuals started receiving Housing First assistance in month 1, the estimates would map out one minus the probability of exiting housing programs.

[32] I cannot rule out completely the possibility that the effect I find is driven by those 10 percent of individuals who are still housed even 30 months after intake.

[33] As discussed in section 3.4, the median days of housing assistance receipt is 320 days in the first 18 months after intake, with approximately 45 percent of treated cases actively receiving housing assistance 18-months after intake.

placement rate increases the duration of housing assistance. Panel (b) plots estimates of the probability that the duration of housing assistance will exceed a given number of days (including zeros) as a function of the case manager placement rate instrument and reveals that a case manager's placement rate effect on the number of days is larger for shorter duration spells and decreases as the duration of housing assistance increases, consistent with case managers having more influence on placement rather duration.

A complementary analysis replaces the endogenous variable of Housing First assistance receipt with the duration of housing assistance but still uses the case manager placement rate as the instrument. As shown by Angrist and Imbens (1995), 2SLS applied to an IV model with variable treatment intensity captures a weighted average of causal responses to a unit change in treatment. In this setting, defining the endogenous regressor as the duration of housing assistance in days permits identification of the effect of another day of housing assistance. Thus, this parameter captures a convex combination of the extensive margin effect of enrollment in a Housing First program and the intensive margin effect of a longer program duration. When estimating this model with days of housing assistance as the endogenous regressor, the results are consistent with those using the binary measure (see Table C.5).

### 5.3 Heterogeneous Effects

#### Individual Characteristics

Table C.6 documents heterogeneous effects of Housing First assistance receipt on crime, health, and homelessness outcomes by individual characteristics. The table presents 2SLS estimates of the effect of Housing First program placement on any return to the homeless system (panel A), any jail booking (panel B), and any DHS service receipt (panel C) for the medium-term (7-18 months after intake) and long term (19-30 months after intake), stratified by observed individual characteristics. Differences in IV results are suggestive of differential impacts of Housing First assistance on these various outcomes.[34]

The estimates in Table C.6 show that, across all subsamples, individuals who receive Housing First assistance are significantly less likely to return to the homeless system, both in the medium- and long-term. However, some subsamples show relatively sizable reductions in crime and DHS services utilization (males, Blacks, young and individuals with prior jail history) compared to others. It is worth noting that some of the large and imprecise implied effects are driven by the small sample sizes, resulting in less estimation power and more noise.

### Short-Term versus Long-Term Rental Subsidy

As a reminder, there are two main types of Housing First programs for individuals experiencing homelessness in Los Angeles County: short- and long-term.[35] To explore whether individuals receiving short-term versus long-term rental subsidies experience different outcomes, I construct two instruments for rapid re-housing and permanent supportive housing assistance receipt in a similar fashion to the original instrument. Specifically, I construct two housing placement rates for each case manager, one for short-term program placements and the other for long-term program placements. The sum of these two instruments gives the original housing placement rate instrument.

In Table C.7, I re-estimate the main IV specification, but with the two separate endogenous variables and instruments described above. I find that individuals who enrolled in either long-term or short-term programs are less likely to return to seek assistance from the homeless support system. Additionally, I find that the likelihood of reductions in future jail bookings and health services utilization is driven by individuals who receive short-term rental subsidies. The results suggest that short-term rental subsidies are very effective, especially when considering prevention of future crimes and emergency health services utilization. However, these results should be interpreted with caution

[34] Additional outcomes on DMH, DPH, and general relief service receipt are available upon request.

[35] See Section 2.1 and Appendix A for a detailed description of these programs.

since the local average treatment effects estimated in IV models with multiple treatments do not have a straightforward interpretation (Kirkeboen et al., 2016; Hull, 2018; Kline and Walters, 2019).

### 5.4 Robustness

*Intakes Per Case Manager.–* Table C.8 examines the sensitivity of the results to alternative minimum case manager intakes required for inclusion in the estimation sample. Column 1 presents the baseline results, including cases whose case manager handled at least 30 cases in 2016-2017. In the next four specifications, I instead require case managers to handle at least 35, 40, 45, or 50 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 manager is too small.

*Fixed Effects Selection.–* Table C.9 examines the sensitivity of the results by allowing the fixed effects within which time period and site are compared to vary. Column 1 presents the baseline results, where case manager assignment is random conditional on service site by month of intake. In the next two specifications, I change the time unit from month to quarter and year, respectively. In columns 4 and 5, I change the location requirement from site to service provider (who might operate several sites) and Service Planning Area of Los Angeles County (which have multiple providers), respectively.[36] These different selections of the level at which cases are compared do not lead to different results from the estimated baseline effects.

*Treatment Timing.–* Table C.10 examines the sensitivity of the results to the definition of treatment. Column 1 presents the baseline results, where Housing First assistance treatment is defined as being enrolled in a Housing First program within six months after intake. In the next four specifications, I instead require that enrollment to Housing First programs occurs within one, three, 12, and 18 months after intake to be considered as treated, respectively. Reassuringly, all treatment timing definitions suggest that housing assistance

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

receipt reduces future homelessness.

*Instrument Specification.*– Table C.11 examines sensitivity to changing how the instrument is constructed. In column 2, I check whether the results are sensitive to outliers by winsorizing the baseline instrument's top and bottom 10 percent values. In column 3, I randomly split the sample in half and used one half to calculate each case manager's average Housing First program placement rate, and use these averages as an instrument for Housing First assistance in the other half of the sample. In column 4, I construct the instrument using all available housing programs, including temporary (emergency) housing programs, to take into account the possibility that case managers differ in their preferences regarding the Housing First approach. Across all these different definitions, the resulting estimates do not materially change.

### 5.5 Exclusion Restriction

Interpreting the IV estimates as the average causal effect of Housing First assistance requires the case manager Housing First program placement rate to affect an individual's outcomes only through the Housing First program placement channel. A potential issue is that case managers may also affect an individual's receipt of emergency housing services (temporary housing programs) and non-housing services intended to support the individual's transition out of homelessness.

To examine the potential impact on individuals' outcomes via emergency housing and non-housing services, I extend the baseline IV model to distinguish between Housing First assistance and these two type of services:

$$H_i = \gamma_H Z^H_{(j)i} + \gamma_E Z^E_{j(i)} + \gamma_S Z^S_{j(i)} + \chi_{sm} + \nu_i \tag{4}$$

$$E_i = \tau_H Z^H_{j(i)} + \tau_E Z^E_{j(i)} + \tau_S Z^S_{j(i)} + \lambda_{sm} + u_i \tag{5}$$

$$S_i = \psi_H Z^H_{j(i)} + \psi_E Z^E_{j(i)} + \psi_S Z^S_{j(i)} + \lambda_{sm} + u_i \tag{6}$$

$$Y_{it} = \beta_t H_i + \gamma_t E_i + \theta_t S_i + \delta_{sm} + X^{'}_i \omega_t + \rho_{it} \tag{7}$$

where $j$ denotes the case manager who handles individual $i$'s case, $H_i$ is an indicator variable equal to 1 if individual $i$ received Housing First assistance, $E_i$ is an indicator variable equal to 1 if individual $i$ received any emergency housing assistance, $S_i$ is an indicator variable equal to 1 if individual $i$ enrolled in any non-housing assistance program, $Z^H_{j(i)}$ denotes the case manager Housing First placement rate, $Z^E_{j(i)}$ denotes the case manager emergency housing placement rate, $Z^S_{j(i)}$ denotes the case manager 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 in the first six months after intake. As in the baseline model, I measure $Z^H_{j(i)}$, $Z^E_{j(i)}$ 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 manager's in providing other types of assistance. In the first case, $Z^H_{j(i)}$ correlates with either $Z^E_{j(i)}$ or $Z^S_{j(i)}$, and $Z^E_{j(i)}$ or $Z^S_{j(i)}$ directly affect $Y_{it}$. 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 $Z^E_{j(i)}$ and $Z^S_{j(i)}$. However, controlling for $Z^E_{j(i)}$ and $Z^S_{j(i)}$ in both (1) and (2) eliminates this source of bias. In the second case, $Z^H_{j(i)}$ correlates with $E_i$ and $S_i$ conditional on $Z^E_{j(i)}$ and $Z^S_{j(i)}$, and $E_i$ or $S_i$ affect $Y_{it}$ holding $H_i$ fixed. 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 $E_i$ and $S_i$. The augmented IV model (4)-(7) addresses this issue by including $E_i$ and $S_i$ as additional endogenous variables and $Z^E_{j(i)}$ and $Z^S_{j(i)}$ as extra instruments.

I examine these two cases and find support for the exclusion restriction. The top panel of Table C.12 repeats the baseline specification for comparison. In panel B, I add the case manager emergency housing placement rate as an additional control in both the first and second stages. In panel C, I add the case manager's emergency housing and non-housing services placement rates as additional controls. The IV estimates for all outcomes are similar to the baseline.

I next estimate the augmented IV model given by (4)-(7). Table C.13 presents the first stage, reduced form, and IV estimates. For the Housing First assistance first stage, the case manager's Housing First placement rate has a coefficient similar to the baseline model. For the other first stages, the case manager's Housing First placement rate has a negative impact on receiving emergency and non-housing services. However, the other instruments have large positive effects. Looking at the reduced form estimates, the case manager Housing First placement rate coefficients are remarkably similar relative to the baseline IV model. Likewise, the IV estimates for Housing First assistance are similar to those from the baseline model, which does not include the emergency housing and non-housing services placement instruments.

## 6 Cost-Benefit Analysis

The most relevant policy implication is whether the positive effects from Housing First programs homeless individuals this study finds are cost-effective and is there a difference in the cost-effectiveness of different housing program types. I attempt to conduct a simple cost-benefit calculation of Housing First programs. My calculations suggest that 50 to 100 percent of average program costs are offset by corresponding benefits in the medium- and long-term, respectively. The benefits tend to be more significant for short-term rental subsidy programs.

Table D.1 presents the results of this cost-benefit analysis exercise. See Appendix D for a detailed description of the exercise. I compute housing assistance costs using data from Los Angeles County (Los Angeles Homelessness Services Authority, 2017). On the benefits side, I measure savings from three broad categories: reduction in homeless services use, reductions in public health and crime costs, and increased employment and reduction in social benefits receipt. Overall, I find that the savings from Housing First offset a substantial portion of Housing First program costs to public agencies in both the 18 and 30 months following intake. I note that these savings are likely to be even more significant, as I ignore the indirect benefits of reducing street homelessness and note that these benefits are likely to accumulate over time and become larger since the cost of homelessness increases exponentially with time (Flaming et al., 2015). In addition, I find that the savings are substantial in both rapid re-housing and permanent supportive housing programs but pay off faster for rapid re-housing programs.

## 7 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. Researchers and policymakers have questioned whether housing assistance is sufficient to treat homelessness and whether the Housing First approach is cost-effective. This study fills this gap in the literature by using novel data and exogenous variation in Housing First assistance receipt to confirm that Housing First programs for homeless individuals have beneficial effects on both housing and non-housing outcomes and that they are cost-effective.

While this paper establishes these fundamental results, several important questions remain for future research. The study's results are inconclusive regarding the effect of Housing First assistance on health. Additional research on the impact of Housing First on different measures of health outcomes is important to better understand if there is a causal relationship between housing and health. Additionally, while I provide some evidence that housing assistance has a beneficial effect on many socioeconomic outcomes, additional evidence would be helpful to assess the external validity of this study's findings, especially concerning income and employment. Finally, the cost-benefit analysis I conduct 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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# 8 Figures

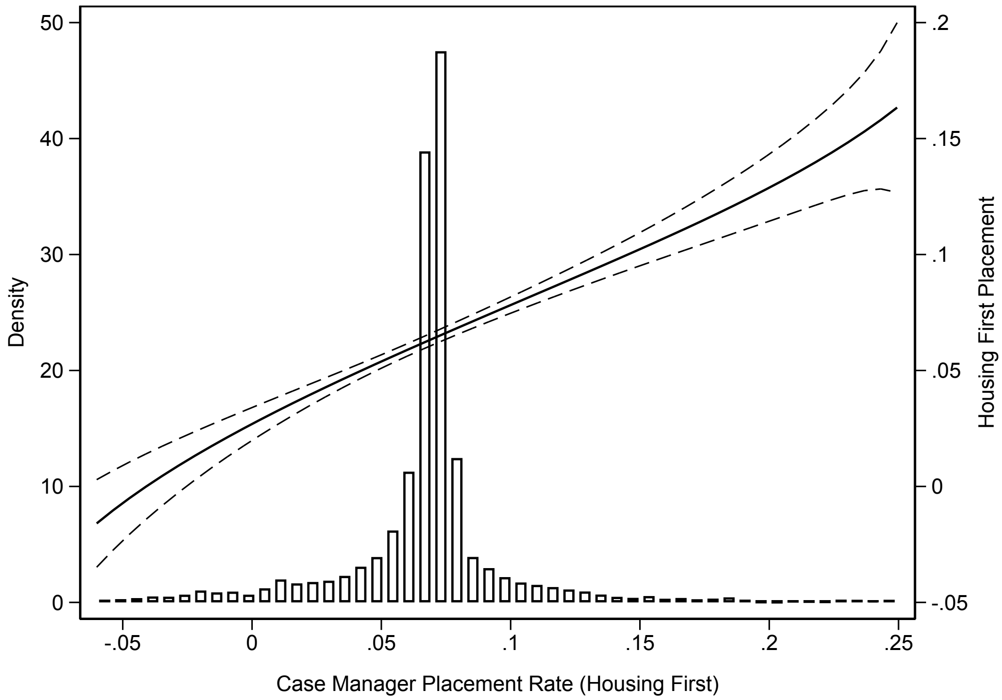
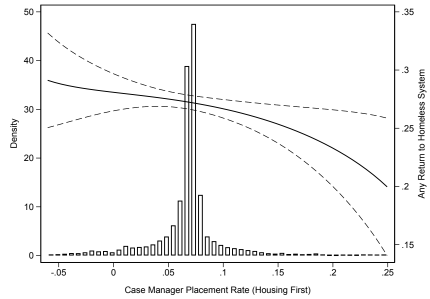
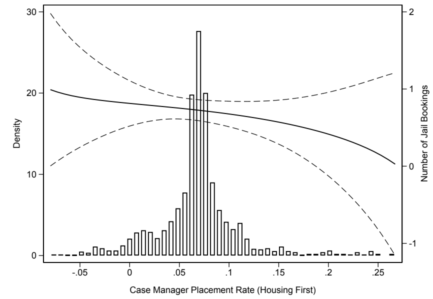



Figure 1. First Stage Graph of Housing First Assistance Receipt on Case Manager Housing First Placement Rate.

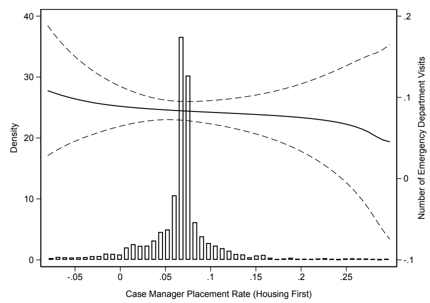
*Notes:* Estimation sample consisting of 15,353 intakes processed in 2016-2017. Probability of permanent housing (Housing First) assistance receipt is plotted on the right y-axis against leave-out mean case manager Housing First placement rate of the assigned case manager shown along the x-axis. The plotted values are mean-standardized residuals from regressions on site x intake month fixed effects and all variables listed in Table 3. The solid line shows a local linear regression of Housing First assistance receipt on case manager Housing First placement rate. Dashed lines show 95% confidence intervals. The histogram shows the density of case manager placement rates along the left y-axis (top and bottom 2% excluded).



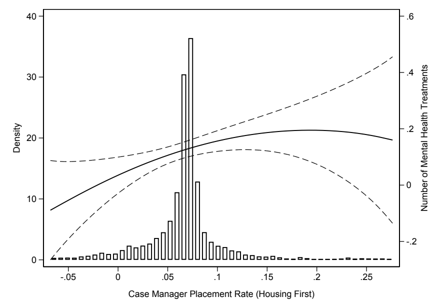

(a) Any Return to Homeless System



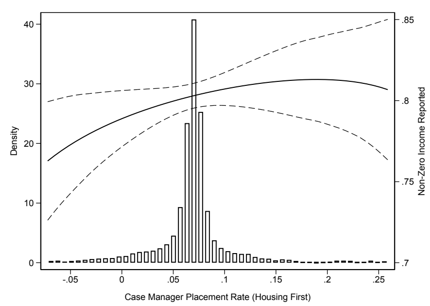

(b) Number of Jail Bookings



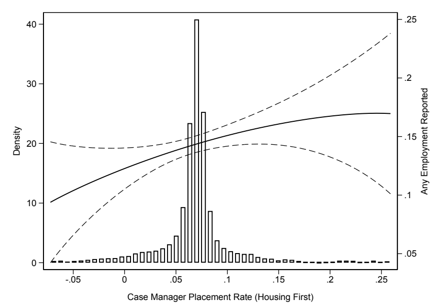

(c) Number of Emergency Department Visits




(d) Number of Mental Health Treatments




(e) Non-Zero Income Reported



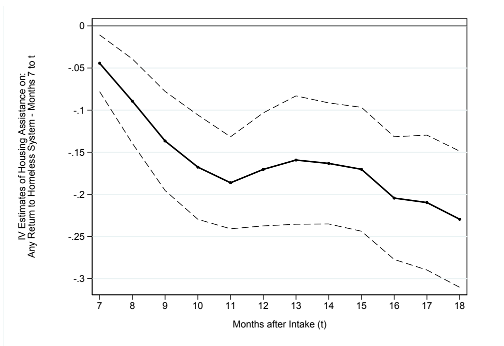

(f) Any Employment Reported

Figure 2. Reduced Form Graphs of Socioeconomic Outcomes on Case Manager Housing Placement Rate.

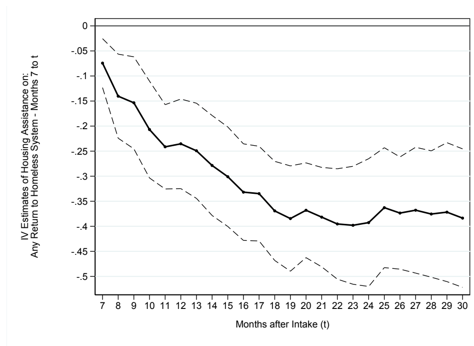
*Notes:* Outcomes of interest (all measured at 7-18 months after intake) are plotted on the right y-axis against leave-out mean case manager Housing First placement rate of the assigned case manager shown along the x-axis. The plotted values are mean-standardized residuals from regressions on site x month fixed effects and all variables listed in Table 3. The solid line shows a local linear regression of the outcome of interest on case manager Housing First placement rate. Dashed lines show 95% confidence intervals. The histogram shows the density of case manager placement rates along the left y-axis (top and bottom 2% excluded).

## I. Medium-Term

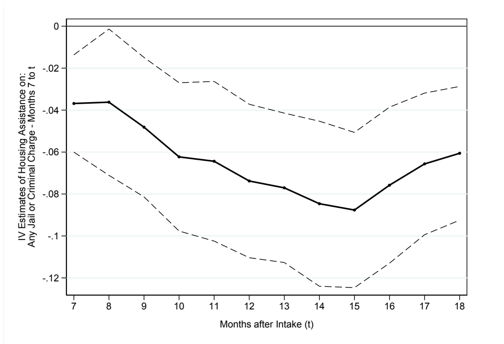
## II. Long-Term



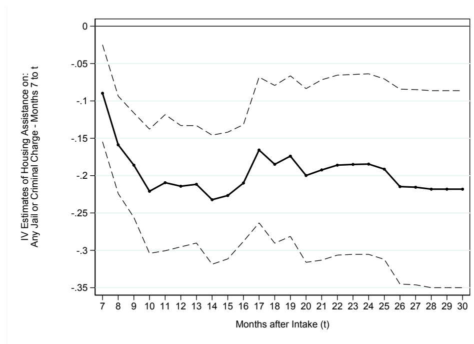

(a) Any Return to Homeless System



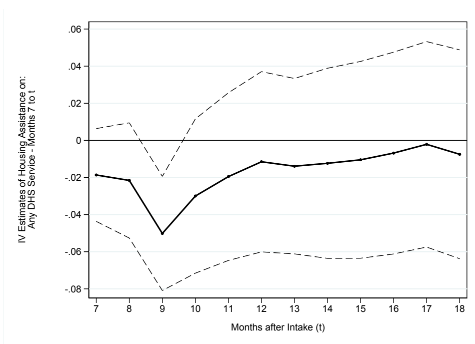

(b) Any Return to Homeless System



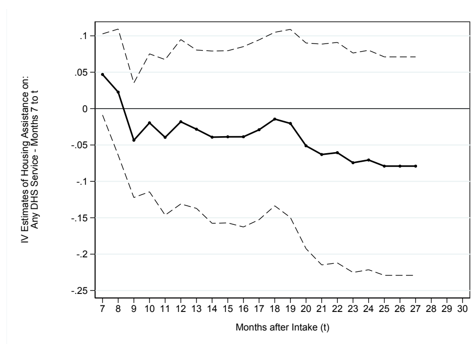

(c) Any Jail Booking or Criminal Charge




(d) Any Jail Booking or Criminal Charge




(e) Any DHS Service




(f) Any DHS Service

Figure 3. IV Estimates of the Effect of Housing First Assistance on Homelessness, Crime, and Health.

*Notes:* The figures present IV estimates of the effect of Housing First assistance on various outcomes. Medium-term outcomes (column 1) are measured at 7-18 months after intake. Long-term outcomes (column 2) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake). Return to the homeless system includes any shelter stay, street outreach event, or a new intake. Dashed lines show 90% confidence intervals.

# 9 Tables

Table 1. Summary Statistics for Baseline Sample.

| | Mean | Std. Dev. | Cases | Mean | Std. Dev. | Cases |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **A. Individual Characteristics:** | | | | | | |
| Age | 44.72 | 11.26 | 15,353 | | | |
| Female | 0.32 | 0.47 | 15,353 | | | |
| Minority (Black or Hispanic) | 0.78 | 0.42 | 15,353 | | | |
| Any homeless history | 0.70 | 0.46 | 15,353 | | | |
| Any reported disability | 0.79 | 0.41 | 15,353 | | | |
| Substance abuse problem | 0.27 | 0.44 | 15,353 | | | |
| Chronic homeless | 0.59 | 0.49 | 15,353 | | | |
| **B. Individual history with public agencies (past 5 years):** | | | | | | |
| Any DHS/DMH/DPH treatment | 0.25 | 0.44 | 15,353 | | | |
| Any interaction with sheriff/probation department | 0.16 | 0.36 | 15,353 | | | |
| Any emergency cash assistance (general releif) | 0.18 | 0.38 | 15,353 | | | |
| Any housing assistance received | 0.04 | 0.19 | 15,353 | | | |
| **C. Homeless Services Received:** | | | | | | |
| Any homeless services | 0.67 | 0.47 | 15,353 | | | |
| Any homeless housing assistance | 0.41 | 0.49 | 15,353 | | | |
| Rental subsidy (Housing First) | 0.07 | 0.25 | 15,353 | | | |
| Short-term rental subsidy (rapid re-housing) | 0.05 | 0.23 | 15,353 | | | |
| Long-term rental subsidy (permanent supportive housing) | 0.01 | 0.11 | 15,353 | | | |
| Temporary (emergency) housing assistance programs | 0.36 | 0.48 | 15,353 | | | |
| Non-housing services | 0.27 | 0.44 | 15,353 | | | |
| **D. Outcomes:** | **Medium-Term (7-18 months after intake)** | | | **Long-Term (19-30 months after intake)** | | |
| Any return to homeless sytem | 0.27 | 0.45 | 15,353 | 0.22 | 0.41 | 8,947 |
| Any emergency shelter stay | 0.14 | 0.34 | 15,353 | 0.10 | 0.30 | 8,947 |
| Any street outreach | 0.12 | 0.33 | 15,353 | 0.11 | 0.31 | 8,947 |
| Any new intake | 0.16 | 0.37 | 15,353 | 0.13 | 0.33 | 8,947 |
| Enrollment in Housing First program | 0.14 | 0.35 | 15,353 | 0.13 | 0.33 | 8,647 |
| Any emergency cash assistance (general relief) | 0.09 | 0.28 | 9,771 | 0.09 | 0.29 | 2,398 |
| Any DHS treatment | 0.07 | 0.26 | 7,401 | 0.05 | 0.21 | 2,235 |
| Any DMH (mental health) treatment | 0.02 | 0.15 | 9,742 | 0.01 | 0.12 | 2,375 |
| Any DPH (substance abuse) treatment | 0.01 | 0.10 | 4,376 | 0.003 | 0.05 | 1,453 |
| Any jail booking | 0.06 | 0.25 | 9,503 | 0.05 | 0.22 | 2,162 |
| Any criminal charge | 0.05 | 0.22 | 9,503 | 0.04 | 0.19 | 2,162 |
| Any probation case | 0.03 | 0.17 | 9,771 | 0.02 | 0.15 | 2,398 |
| Any Income (non-zero) Reported | 0.80 | 0.40 | 5,854 | 0.79 | 0.40 | 2,592 |
| Any Employment Reported | 0.14 | 0.35 | 5,854 | 0.12 | 0.33 | 2,592 |
| Any Social Benefits Receipt Reported | 0.70 | 0.46 | 5,854 | 0.70 | 0.46 | 2,592 |

*Notes:* Panels A,B, and C show sample means (column 1), standard deviations (column 2), and number of cases (column 3) for the baseline sample of cases. Medium-term outcomes (columns 1-3 of panel D) are measured at 7-18 months after intake. Long-term outcomes (columns 4-6 of panel D) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake) and DPH (19-23 months after intake). Chronic homeless is defined as having homeless history and substantial disability. Return to system includes any shelter stay, street outreach event, or a new intake.

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Controls:** | Site X Time FEs | Add Demographics | Add Acuity Measures | Add History of Interaction with Public Agencies |
| **Dependent Variable: Housing First Program Placement:** | | | | |
| Case Manager Housing First Placement Rate | 0.856 | 0.852 | 0.848 | 0.847 |
| | (0.0647) | (0.0644) | (0.0632) | (0.0631) |
| F-stat. (Instrument) | 174.74 | 175.07 | 180.33 | 180.52 |
| Dependent mean | 0.066 | 0.066 | 0.066 | 0.066 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 15,353 |

*Notes:* Columns 1-4 show first stage estimates of different specifications on the baseline sample of cases. Column 1 includes site-month of intake fixed effects. Column 2 adds the individual demographics listed in Table 3. Column 3 adds acuity measures listed in Table 3. Column 4 adds lagged outcomes variables described in Table 3. Standard errors are clustered at the case manager level.

Table 3. Testing for Random Assignment of Homeless Cases to Case Managers.

| Dependent Variable: | Housing First Placement Rate | |
|---|---|---|
| | (1) Coefficient Estimate | (2) Standard Error |
| **Demographics:** | | |
| Age | -0.000251 | (0.000312) |
| Age-squared | 0.000001 | (0.000004) |
| Female | 0.000882 | (0.00141) |
| Black | 0.00527 | (0.00280) |
| Hispanic | 0.00257 | (0.00240) |
| Non-Hispanic White | 0.000980 | (0.00282) |
| **Acuity Assessment:** | | |
| Homeless history | 0.00306 | (0.00240) |
| Any disability | 0.00142 | (0.00188) |
| Chronic homeless | -0.00434 | (0.00356) |
| Substance abuse | -0.00245 | (0.00246) |
| Health emergency in last 6 months | -0.000769 | (0.00147) |
| Jail/prison in last 6 months | -0.00219 | (0.00175) |
| **Past Health, Criminal, Housing History:** | | |
| Any DHS treatment in past 5 years | -0.00255 | (0.00157) |
| Any DMH treatment in past 5 years | -0.000405 | (0.00198) |
| Any DPH (substance abuse) treatment in past 5 years | 0.000261 | (0.00216) |
| Involvement with Sheriff's department in past 5 years | -0.000590 | (0.00172) |
| Involvement with Probation department in past 5 years | -0.00214 | (0.00218) |
| Any emergency cash assistance (general relief) in past 5 years | 0.00129 | (0.00143) |
| Any housing assistance recieved in past 5 years | -0.00317 | (0.00204) |
| F-statistic for joint test | 0.748 | |
| p-value | 0.766 | |
| Number of Cases | 15,353 | |

*Notes:* Columns 1-2 show estimates for baseline sample of homeless cases. The estimation includes controls for site x month of intake 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 clustered at the case manager level.

Table 4. The Effect of Housing First Assistance on Crime, Health, and Homelessness Outcomes.

| | Housing Stability and Homelessness Outcomes | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Return to Homeless System (1) | Emergency Shelter (2) | Street Outreach (3) | New Intake (4) | Continued Enrollment (5) | General Relief (6) |
| **A. Medium-Term (7-18 Months After Intake)** | | | | | | |
| RF: Housing First Placement Rate | -0.195 | -0.0846 | -0.0746 | -0.0731 | 0.445 | -0.0626 |
| | (0.0379) | (0.0214) | (0.0385) | (0.0258) | (0.0666) | (0.0270) |
| 2SLS: Housing First Placement | -0.230 | -0.0998 | -0.0881 | -0.0863 | 0.525 | -0.0749 |
| | (0.0490) | (0.0253) | (0.0474) | (0.0307) | (0.0636) | (0.0351) |
| Dependent Mean | 0.27 | 0.14 | 0.12 | 0.16 | 0.14 | 0.09 |
| Number of Cases | 15,353 | 15,353 | 15,353 | 15,353 | 15,353 | 9,771 |
| **B. Long-Term (19-30 Months After Intake)** | | | | | | |
| RF: Housing First Placement Rate | -0.124 | -0.0502 | -0.0746 | -0.0534 | 0.138 | -0.138 |
| | (0.0544) | (0.0352) | (0.0444) | (0.0322) | (0.0555) | (0.0660) |
| 2SLS: Housing First Placement | -0.153 | -0.0621 | -0.0922 | -0.0660 | 0.171 | -0.165 |
| | (0.0623) | (0.0436) | (0.0515) | (0.0382) | (0.0628) | (0.0812) |
| Dependent Mean | 0.22 | 0.10 | 0.11 | 0.13 | 0.13 | 0.09 |
| Number of Cases | 8,947 | 8,947 | 8,947 | 8,947 | 8,947 | 2,398 |

| | Crime Outcomes | | | Health Outcomes | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Jail Booking | Criminal Charge | Probation | Any DHS | Any DMH | Any DPH |
| **C. Medium-Term (7-18 Months After Intake)** | | | | | | |
| RF: Housing First Placement Rate | -0.0498 | -0.0363 | 0.00406 | -0.00610 | -0.00115 | -0.0335 |
| | (0.0170) | (0.0165) | (0.0115) | (0.0277) | (0.0171) | (0.0182) |
| 2SLS: Housing First Placement | -0.0606 | -0.0442 | 0.00486 | -0.00749 | -0.00137 | -0.0381 |
| | (0.0193) | (0.0197) | (0.0139) | (0.0341) | (0.0204) | (0.0206) |
| Dependent Mean | 0.06 | 0.05 | 0.03 | 0.07 | 0.02 | 0.01 |
| Number of Cases | 9,503 | 9,503 | 9,771 | 7,401 | 9,742 | 4,376 |
| **D. Long-Term (19-30 Months After Intake)** | | | | | | |
| RF: Housing First Placement Rate | -0.0972 | -0.0537 | -0.0353 | -0.0970 | 0.0381 | 0.00972 |
| | (0.0306) | (0.0253) | (0.0338) | (0.0524) | (0.0218) | (0.0183) |
| 2SLS: Housing First Placement | -0.130 | -0.0721 | -0.0419 | -0.124 | 0.0450 | 0.0206 |
| | (0.0509) | (0.0362) | (0.0408) | (0.0673) | (0.0280) | (0.0455) |
| Dependent Mean | 0.05 | 0.04 | 0.02 | 0.05 | 0.01 | 0.003 |
| Number of Cases | 2,162 | 2,162 | 2,398 | 2,235 | 2,375 | 1,453 |

*Notes:* Medium-term outcomes (panels A and C) are measured at 7-18 months after intake. Long-term outcomes (panels B and D) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake) and DPH (19-23 months after intake). Return to system includes any shelter stay, street outreach event, or a new intake. Continued enrollment is an indicator for enrollment in a Housing First program at any point between 7-18 (19-30) months after intake. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Table 5. The Effect of Housing First Assistance on Income, Employment, and Social Benefits.

| | Income | | Employment | | Social Benefits | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Any Income | Monthly Income | Employed | Monthly Wages | Any Benefits | Monthly Benefits |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **A. Medium-Term (7-18 Months After Intake)** | | | | | | |
| RF: Housing First Placement Rate | 0.170 | 687 | 0.421 | 756 | -0.234 | -79 |
| | (0.0657) | (152) | (0.0900) | (173) | (0.115) | (77) |
| 2SLS: Housing First Placement | 0.177 | 715 | 0.436 | 783 | -0.244 | -82 |
| | (0.0690) | (161) | (0.0889) | (178) | (0.117) | (79) |
| Dependent Mean | 0.80 | 616 | 0.14 | 198 | 0.70 | 417 |
| Number of Cases | 5,709 | 5,709 | 5,960 | 5,960 | 5,709 | 5,709 |
| **B. Long-Term (19-30 Months After Intake)** | | | | | | |
| RF: Housing First Placement Rate | 0.295 | 450 | 0.314 | 284 | 0.0944 | 181 |
| | (0.124) | (395) | (0.0928) | (314) | (0.162) | (153) |
| 2SLS: Housing First Placement | 0.420 | 640 | 0.453 | 410 | 0.134 | 257 |
| | (0.169) | (566) | (0.139) | (463) | (0.227) | (209) |
| Dependent Mean | 0.79 | 668 | 0.11 | 169 | 0.71 | 486 |
| Number of Cases | 2,461 | 2,461 | 2,717 | 2,717 | 2,461 | 2,461 |

*Notes:* Medium-term outcomes (panels A and C) are measured at 7-18 months after intake. Long-term outcomes (panels B and D) are measured at 19-30 months after intake. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

# The Effect of Housing First Programs on Future Homelessness and Socioeconomic Outcomes

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**Appendix Material - For Online Publication Only**

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# 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.[37] Panel (a) includes both unsheltered and sheltered homeless individuals, while panel (b) includes only unsheltered homeless individuals.[38] 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.[39]

[37]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.

[38]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).

[39]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.

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.

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; 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).[40]

Columns 3-4 of Table A.1 compare the characteristics of single individuals

[40]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., 2020).

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.[41] 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 (United States Interagency Council on Homelessness, 2019). 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 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. 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.[42] As a result, for example, the county's overall

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

[42] County voters have supported increasing homeless spending by approving billions of

budget for homelessness in 2018 was $619 million (Smith, 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 even after housing subsidy has ended. The three main permanent housing programs are Rapid Re-Housing, Permanent

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.

Supportive Housing, and Other Permanent Housing.

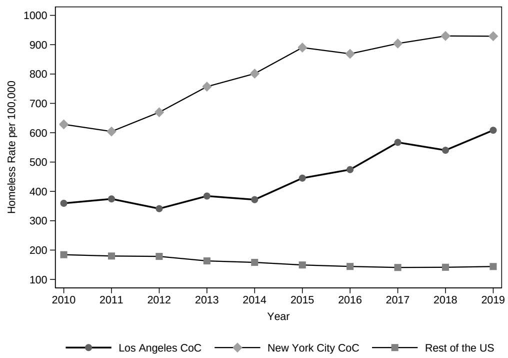
In Los Angeles CoC, as of 2019, there was a total of 45,116 beds in 764 housing assistance programs that serve the homeless or previously homeless population (Los Angeles Homeless Services Authority, 2019). 25,608 (57%) beds in 630 programs serve the single adult homeless population, and the rest serve 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.

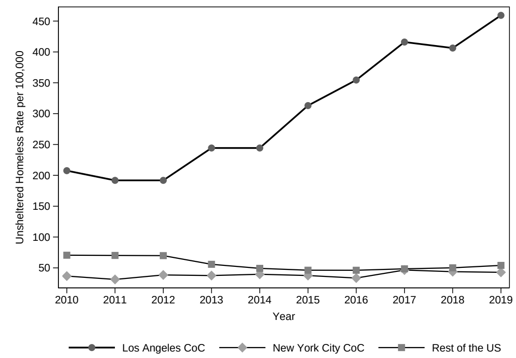
Finally, it is important to note that many housing assistance programs offer non-housing services as well to support the rehabilitation process of participants, especially in permanent housing programs. In addition, the homeless support system offers additional non-housing assistance programs.[43] The most

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

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.



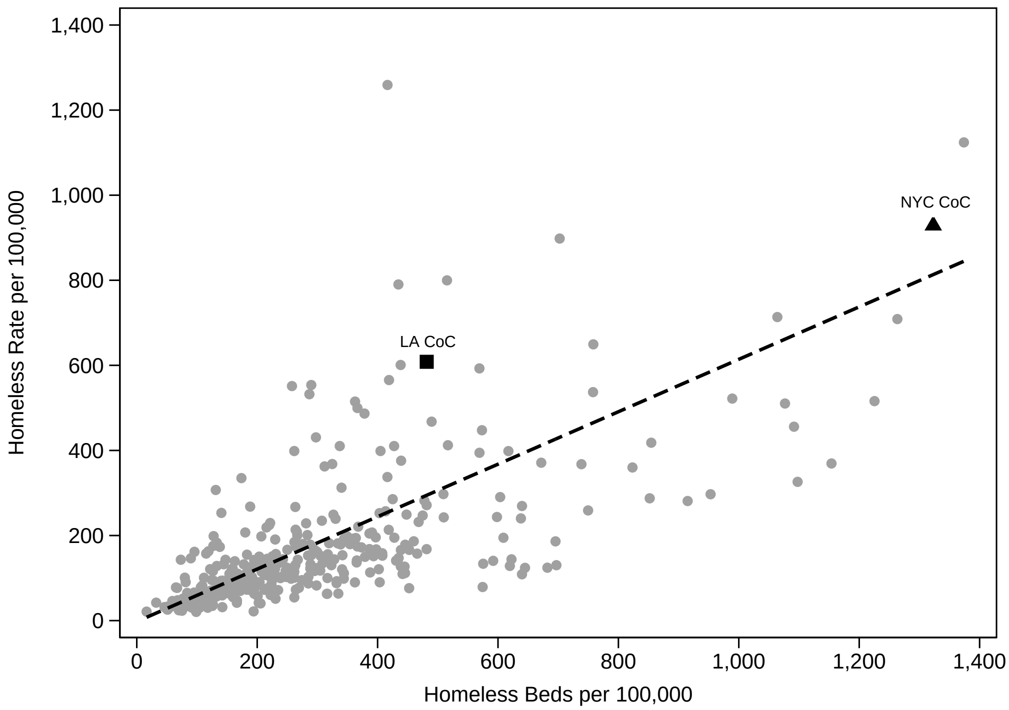

(a) Overall Homeless Rate




(b) Unsheltered Homeless Rate

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

*Notes:* 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).




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

*Notes:* 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).

Appendix 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 | - | - |

*Notes:* 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).

# 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.

Appendix 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)<br>- Acuity indicators (homeless history, disabilities)<br>- Location of intake (SPA)<br>- Intake Date | 01/2016-12/2018 |
| | - Case manager name<br>- Agency name | 01/2016-02/2018 |
| | (2) Homeless Management Information System (HMIS) | 01/2010-06/2019 |
| | - Homeless programs placements (housing and non-housing)<br>- Program start date and end date (when relevant)<br>- Program information (agency, name, type)<br>- 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<br>- 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<br>- 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)<br>- 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<br>- Homelessness Indicator | |
| | (7) Los Angeles County Sheriff Department (LASD) | 04/2005-08/2018 |
| | - Criminal charges<br>- Arrests<br>- Incarceration history | |
| | (8) Los Angeles County Department of Probation | 01/2005-08/2018 |
| | - Start and end date of probation service | |

*Notes:* 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 manager 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 managers 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 managers 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.[44]

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 con-

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

tract 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 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.[45]

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.

[45] 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.

### 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.

## 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. Keep intakes conducted in 2016-2017.

4. Drop duplicates or multiple same-day intakes.

5. Drop cases with maissing case manager, organization, and site information.

6. Keep intakes conducted for single adults age 25-65 with non-missing demographics.

7. Clean agency and case manager names and assign identifiers.

   (a) Agency and case manager 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 managers to work on multiple agencies).

   (d) Link clean agency and case-worker identifiers to main intake data.

   (e) Overall, there are 313 sites (defined as agency-area combination) and 2,988 unique case managers.

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

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

10. Keep case managers with more than 30 non-veteran cases handled in 2016-2017. I impose this restriction to avoid concerns regarding small cell sizes.

11. Keep site-month cells with more than one observation.

### 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 emergency shelter stay, 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. 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.

### B.4 Sample Restrictions

Starting from the raw dataset of intakes, I make a series of restrictions to obtain the baseline sample of intakes. First, I focus on intakes conducted in 2016-2017 to follow all cases for at least 18 months after intake. Second, I remove duplicates and intakes for the same individual by different case managers on the same day. Third, I remove individuals with missing information on the case manager, organizational affiliation, or intake location. Fourth, I limit attention to single adults aged 25-65 with non-missing demographics. Finally, I remove veteran cases because homeless veterans are redirected to the United States

Veterans Administration Homeless System for further treatment. Hence, their case manager assignment is not relevant to whether they receive housing .[46]

The resulting sample of intakes is used to measure a case manager's share of cases that ended up enrolling in a Housing First program, which serves as the instrument for the treatment. Next, I impose two additional restrictions to set up the baseline estimation sample such that it only contains intakes that were as-good-as-randomly assigned to case managers. Specifically, I restrict attention to service sites that had at least two case managers working each month and case managers who handled at least 30 cases in 2016-2017. Finally, I restrict the sample to individuals' first intake with the homeless system. These restrictions result in 15,353 individuals, for which this is their first interaction with the homeless system in Los Angeles County. Table C.1 shows how the various restrictions affect the number of cases, clients, case managers and service sites.

## B.5 Description of Treatment and Outcome Variables Used in the Analysis

I summarize the key treatment and outcome measures relevant for the analysis of the impact of case managers and Housing First programs on individuals experiencing homelessness.

*Housing First (Any Rental Subsidy).*– The baseline treatment is defined as enrollment in any Housing First program that provides rental subsidy (i.e., rapid re-rehousing, permanent supportive housing, or other permanent housing programs) at any point during the first 6-months after intake. This measure excludes any continuum programs (i.e., emergency shelters and transitional housing) for two reasons. First, individuals in continuum programs are considered homeless since they do not have a permanent housing solution. Second, one of the main challenges in the homelessness literature is to investigate the impact of Housing First programs on individuals' outcomes and to compare them to those of traditional continuum programs (Burt et al., 2001; Kertesz

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

and Johnson, 2017). Furthermore, treatment is censored at 6-months from intake date to balance two opposing empirical challenges. First, waiting times for Housing First programs are usually very long. This implies that the treatment start date is different from the intake date for the majority of cases. Second, the data does not indicate whether a housing placement is linked directly to the case manager handling the individual during intake. As a result, the longer the time passes from intake to enrollment, the lower the likelihood that the case manager is directly responsible for the placement.[47]

*Emergency Shelter Stays.–* This outcome measure is defined as enrollment in any emergency shelter program at any point after intake.[48] This measure of housing stability is used extensively in the homelessness literature since emergency shelters provide interim housing solutions for currently homeless people. It is based on the idea that individuals experiencing homelessness are likely to seek assistance from emergency shelters. Additionally, emergency shelter enrollments are one of a very limited set of administrative data that is collected on individuals experiencing homelessness. (Evans et al., 2016; Gubits et al., 2018).

*Any Street Outreach Event.–* This outcome measure is defined as enrollment in any street outreach program at any point after intake. Street outreach programs identify and engage individuals who are unsheltered in order to connect them to services and move them toward regaining permanent housing (Weare, 2021). Hence, it provides another source of administrative data collected on individuals experiencing homelessness who are unsheltered.

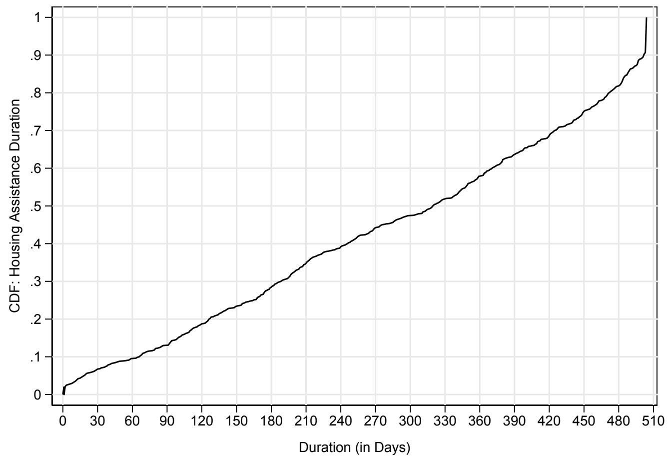
*Any New Case Intake.–* This outcome measure is defined as having an intake and new case opening for an individual by a new case manager at any point after the first intake. Individuals who reach out to different service providers if they become homeless again have a new case opened for them.

[47] In practice, approximately 60 percent (90 percent) of Housing First program enrollments occur within the first six-month (year) after intake. Censoring the treatment at 1-month, 3-months, 12-months, and 18-months after intake does not materially change results.

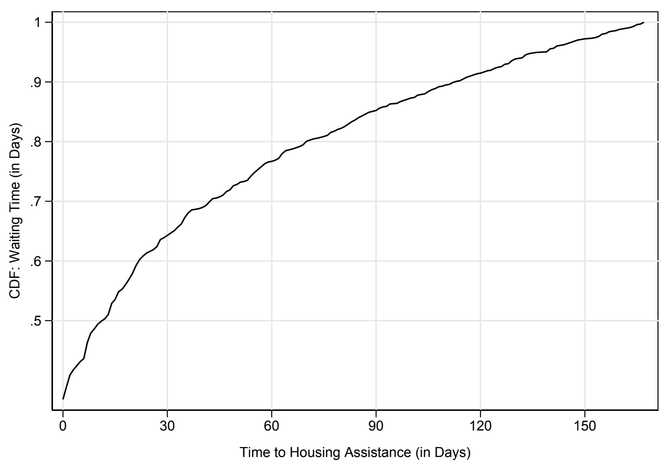
[48] The main outcome of the paper will focus on any visits between 7-18 (medium-term) and 19-30 (long-term) months after intake. This is true for the rest of the outcomes in the analysis as well.

*Continued Enrollment in Housing Program.*– Individuals receiving housing assistance can struggle to maintain eligibility or adjust to living in a stable housing situation (Nuttbrock et al., 1997; Veldhuizen et al., 2015). Maintaining eligibility in a housing program is thus considered a successful outcome for many individuals, especially those receiving an indefinite rental subsidy. This outcome measure is defined as being enrolled in a permanent housing program at any point after intake.

# C Appendix Figures and Tables



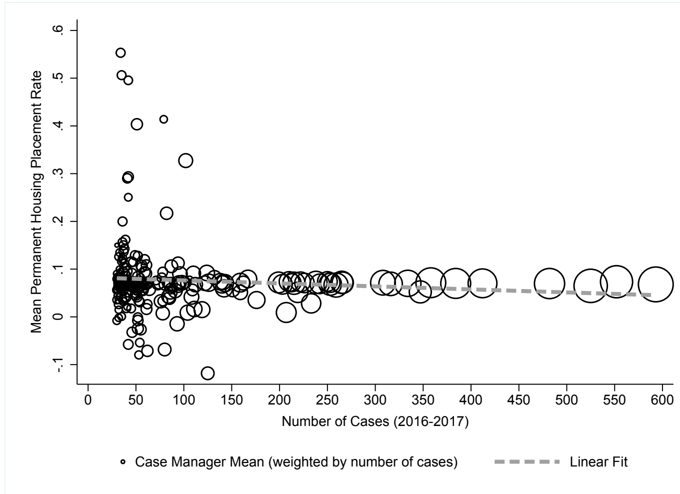

(a) Days in Housing First Programs - CDF



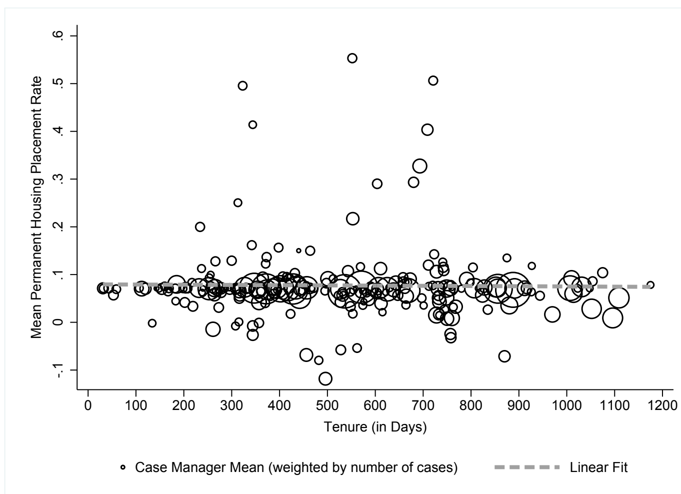

(b) Waiting Time (in Days) to Housing First - CDF

Appendix Figure C.1. Housing First Assistance Duration and Wait Time.

*Notes:* Figure (a) shows the CDF of the duration of Housing First assistance (in days) in the first 18-months after intake. Figure (b) shows the CDF of the waiting time (in days) until enrollment to Housing First program. The sample used to prepare these figures consists of 1,008 cases which received Housing First assistance within six months after intake.




(a) Number of Cases



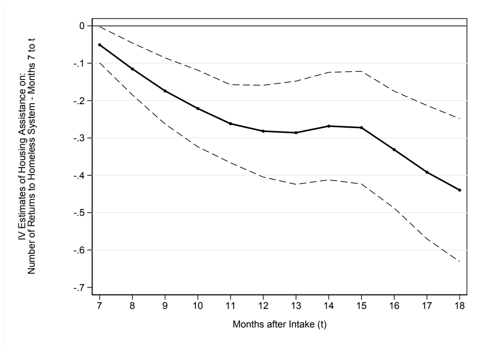

(b) Tenure

Appendix Figure C.2. Case Manager Housing First Placement Rate versus Number of Cases and Tenure.

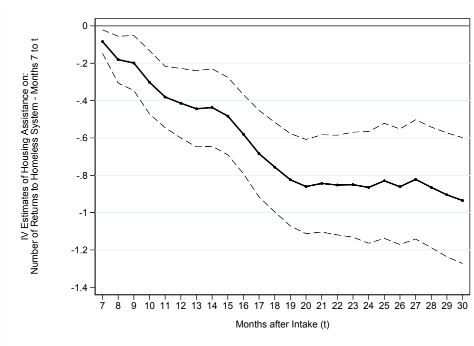
*Notes:* Panel (a) plots case manager Housing First placement rate against the total number of cases handled by each case manager in 2016-2017. Panel (b) plots case manager Housing First placement rate against the proxy for tenure (in days) of each case manager. Tenure is defined as the number of days between the case manager's first and last observed cases. There are 236 unique case managers, and on average, each case manager has handled a total of 200 cases in 2016-2017. Housing First placement rates are standardized by subtracting off service site by month of intake means and case level covariates. Dot size is proportional to the number of cases the case manager has in the estimation sample, which is slightly smaller than the overall number of cases.

## I. Medium-Term

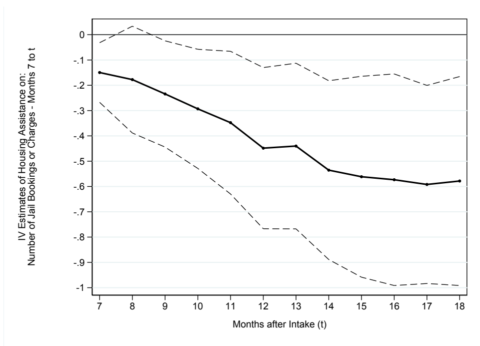
## II. Long-Term



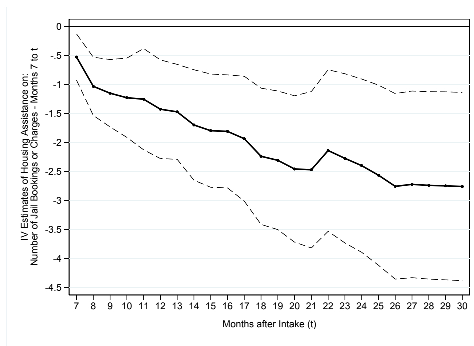

(a) Number of Returns to Homeless System



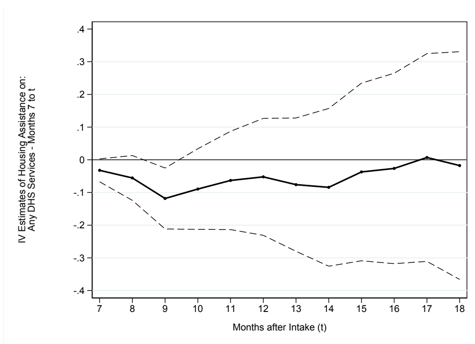

(b) Number of Returns to Homeless System



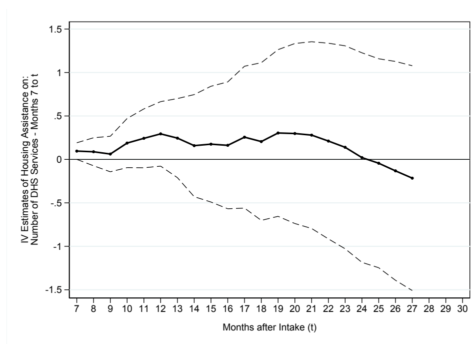

(c) Number of Jail Bookings/Criminal Charges




(d) Number of Jail Bookings/Criminal Charges



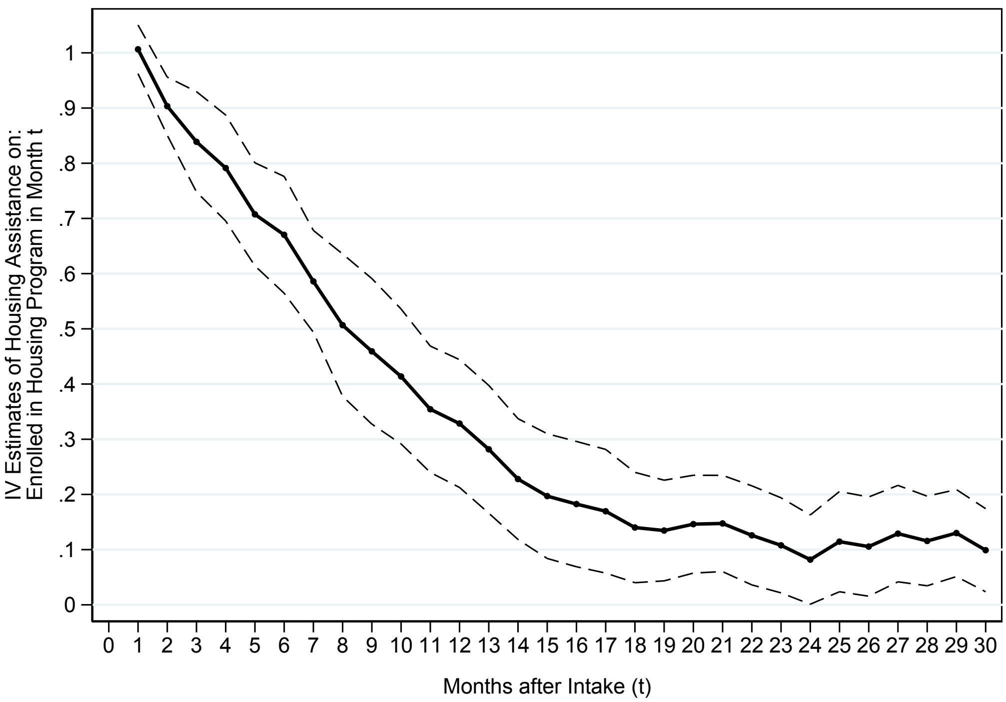

(e) Number of DHS Services




(f) Number of DHS Services

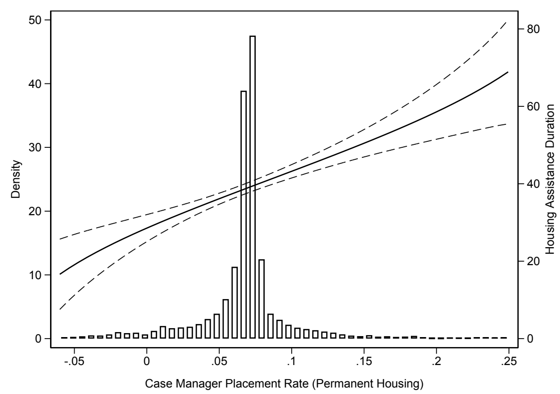
Appendix Figure C.3. IV Estimates of the Effect of Housing First Assistance on Intensive Margin Outcomes.

*Notes:* The figures present IV estimates of the effect of Housing First assistance on various outcomes. Medium-term outcomes (column 1) are measured at 7-18 months after intake. Long-term outcomes (column 2) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake). Return to the homeless system includes any shelter stay, street outreach event, or a new intake. Dashed lines show 90% confidence intervals.

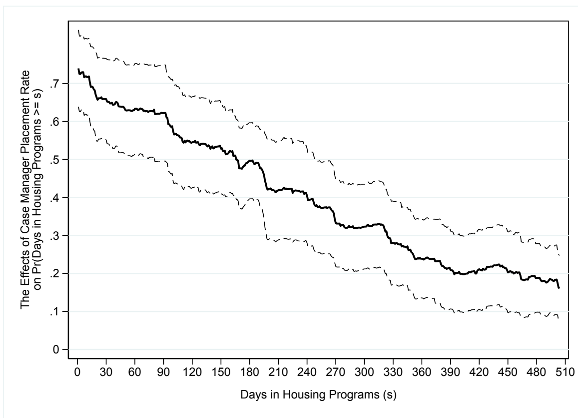



Appendix Figure C.4. IV Estimates of the Effect of Housing First Assistance on Future Enrollment in Housing First Programs.

*Notes:* Estimation sample consisting of 15,353 intakes processed in 2016-2017. The figure plots the IV estimates of Housing First assistance (within 6 months after intake) on the probability of being enrolled in a Housing First program in month $t$ after intake. Dashed lines show 90% confidence intervals.




(a) IV Estimates: Days in Housing First Programs - Months 1 to $t$




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

Appendix Figure C.5. First Stage Graphs of Housing First Assistance Duration on Case Manager Placement Rate.

*Notes:* Estimation sample consisting of 15,353 intakes processed in 2016-2017. Days in Housing First programs is plotted on the right y-axis against leave-out mean case manager Housing First program placement rate in panel (a) of the assigned case manager is shown along the x-axis. The plotted values are mean-standardized residuals from regressions on service site x month of intake fixed effects and all variables listed in Table 3. The solid line shows a local linear regression of days in Housing First programs on case manager placement rate. The histogram in panel (a) shows the density of case manager placement rate along the left y-axis (top and bottom 2% excluded). Panel (b) shows the estimates of case manager placement rate on Pr(Days in Housing First Programs $\geq t$). Dashed lines show 90% confidence intervals.

Appendix Table C.1. Sample Restrictions.

| | Sample Sizes (Remaining after each restriction): | | | |
|---|---|---|---|---|
| | Number of Intakes | Number of Individuals | Number of Case Managers | Number of Sites |
| | (1) | (2) | (3) | (4) |
| **All Cases:** | 87,500 | 67,171 | - | - |
| Keep all intakes conducted in 2016-2017 | 55,509 | 42,665 | - | - |
| Remove duplicates or multiple same-day intakes | 53,414 | 42,182 | - | - |
| Drop cases with missing case manager, organization, and site information | 52,286 | 41,490 | 2,988 | 313 |
| Keep single adults age 25-65 with non-missing demographics | 38,414 | 29,610 | 2,623 | 285 |
| Keep all non-veteran cases | 32,376 | 24,956 | 2,207 | 252 |
| Keep sites with at least 2 case managers in a given month | 29,891 | 23,226 | 1,970 | 128 |
| Keep case managers with more than 30 non-veteran intakes | 20,333 | 16,638 | 237 | 71 |
| Keep individuals' first case with the homeless system | 15,467 | 15,467 | 237 | 71 |
| Keep site-month cells with more than one observation | 15,353 | 15,353 | 236 | 70 |

*Notes:* The initial sample consists of all single adults' intakes processed in Los Angeles County's homeless support system from 2016 to 2018.

Appendix Table C.2. Cross-Sectional Correlations Between Crime, Health, and Homelessness Outcomes and Housing First Assistance.

| | Housing Stability and Homelessness Outcomes | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Return to Homeless System (1) | Emergency Shelter (2) | Street Outreach (3) | New Intake (4) | Continued Enrollment (5) | General Relief (6) |
| **A. Medium-Term (7-18 Months After Intake)** | | | | | | |
| OLS: Housing First Placement | -0.150 | -0.112 | -0.0594 | -0.0932 | 0.691 | -0.0157 |
| *No Controls* | (0.0150) | (0.00958) | (0.00936) | (0.0115) | (0.0221) | (0.0106) |
| OLS: Housing First Placement | -0.144 | -0.0872 | -0.0657 | -0.0957 | 0.652 | -0.0130 |
| *All Controls* | (0.0175) | (0.0113) | (0.0122) | (0.0131) | (0.0225) | (0.0115) |
| Dependent Mean | 0.27 | 0.14 | 0.12 | 0.16 | 0.14 | 0.09 |
| Number of Cases | 15,353 | 15,353 | 15,353 | 15,353 | 15,353 | 9,771 |
| **B. Long-Term (19-30 Months After Intake)** | | | | | | |
| OLS: Housing First Placement | -0.0724 | -0.0609 | -0.0338 | -0.0331 | 0.277 | 0.0111 |
| *No Controls* | (0.0161) | (0.00929) | (0.0128) | (0.0125) | (0.0230) | (0.0224) |
| OLS: Housing First Placement | -0.0674 | -0.0358 | -0.0287 | -0.0366 | 0.261 | -0.000645 |
| *All Controls* | (0.0168) | (0.0103) | (0.0144) | (0.0139) | (0.0228) | (0.0193) |
| Dependent Mean | 0.22 | 0.10 | 0.11 | 0.13 | 0.13 | 0.09 |
| Number of Cases | 8,947 | 8,947 | 8,947 | 8,947 | 8,947 | 2,398 |
| | **Crime Outcomes** | | | **Health Outcomes** | | |
| Dependent Variable: | Jail Booking | Criminal Charge | Probation | Any DHS | Any DMH | Any DPH |
| **C. Medium-Term (7-18 Months After Intake)** | | | | | | |
| OLS: Housing First Placement | -0.00260 | 0.00481 | -0.00578 | -0.00753 | -0.00986 | 0.00284 |
| *No Controls* | (0.00975) | (0.00910) | (0.00544) | (0.0100) | (0.00432) | (0.00581) |
| OLS: Housing First Placement | -0.00365 | 0.00377 | -0.00873 | -0.00138 | -0.0159 | 0.00261 |
| *All Controls* | (0.0101) | (0.00901) | (0.00557) | (0.0110) | (0.00536) | (0.00549) |
| Dependent Mean | 0.06 | 0.05 | 0.03 | 0.07 | 0.02 | 0.01 |
| Number of Cases | 9,503 | 9,503 | 9,771 | 7,401 | 9,742 | 4,376 |
| **D. Long-Term (19-30 Months After Intake)** | | | | | | |
| OLS: Housing First Placement | 0.0299 | 0.0152 | 0.0135 | 0.0175 | 0.00494 | 0.0125 |
| *No Controls* | (0.0217) | (0.0154) | (0.0113) | (0.0161) | (0.00953) | (0.00960) |
| OLS: Housing First Placement | 0.0254 | 0.0122 | 0.00492 | 0.0109 | 0.000480 | 0.0107 |
| *All Controls* | (0.0220) | (0.0157) | (0.0117) | (0.0156) | (0.0106) | (0.0101) |
| Dependent Mean | 0.05 | 0.04 | 0.02 | 0.05 | 0.01 | 0.00 |
| Number of Cases | 2,162 | 2,162 | 2,398 | 2,235 | 2,375 | 1,453 |

*Notes:* Medium-term outcomes (panels A and C) are measured at 7-18 months after intake. Long-term outcomes (panels B and D) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake) and DPH (19-23 months after intake). Return to system includes any shelter stay, street outreach event, or a new intake. Continued enrollment is an indicator for enrollment in a rental subsidy (Housing First) program at any point between 7-18 (19-30) months after intake. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.3. Tests for the Monotonicity Assumption.

| Dependent Variable: | Housing First Program Enrollment | | | |
|---|---|---|---|---|
| Instrument Type: | **Baseline** | **Reverse-Sample** | **Baseline** | **Reverse-Sample** |
| | (1) | (2) | (3) | (4) |
| **A. Chronic Homeless Status** | | | | |
| **Subsample:** | **Chronic Homeless** | | **Not Chronic Homeless** | |
| Estimate | 0.848 | 0.575 | 0.679 | 0.643 |
| (SE) | (0.0551) | (0.0676) | (0.121) | (0.118) |
| Dependent Mean | 0.06 | 0.07 | 0.06 | 0.06 |
| Number of Cases | 8,918 | 8,706 | 6,224 | 6,224 |
| **B. Age** | | | | |
| **Subsample:** | **Age at Intake <=45** | | **Age at Intake > 45** | |
| Estimate | 0.872 | 0.843 | 0.797 | 0.668 |
| (SE) | (0.0852) | (0.0841) | (0.0711) | (0.0670) |
| Dependent Mean | 0.06 | 0.06 | 0.07 | 0.07 |
| Number of Cases | 7,340 | 7,340 | 7,765 | 7,765 |
| **C. Gender** | | | | |
| **Sub-sample:** | **Males** | | **Females** | |
| Estimate | 0.824 | 0.645 | 0.849 | 0.758 |
| (SE) | (0.0769) | (0.0755) | (0.0768) | (0.0877) |
| Dependent Mean | 0.05 | 0.06 | 0.09 | 0.09 |
| Number of Cases | 10,308 | 9,185 | 4,796 | 4,573 |
| **D. Race** | | | | |
| **Subsample:** | **Blacks** | | **Not Blacks** | |
| Estimate | 0.800 | 0.604 | 0.878 | 0.773 |
| (SE) | (0.0809) | (0.0831) | (0.0837) | (0.0687) |
| Dependent Mean | 0.07 | 0.07 | 0.06 | 0.06 |
| Number of Cases | 7,879 | 7,870 | 7,231 | 7,170 |
| **E. Ethnicity** | | | | |
| **Subsample:** | **Hispanics** | | **Not Hispanics** | |
| Estimate | 0.967 | 0.995 | 0.786 | 0.508 |
| (SE) | (0.116) | (0.0954) | (0.0634) | (0.0686) |
| Dependent Mean | 0.05 | 0.05 | 0.07 | 0.07 |
| Number of Intakes | 3,704 | 3,704 | 11,417 | 11,348 |

*Notes:* Estimation sample of all intakes processed in 2016-2017. Controls include all variables listed in Table 3, including controls for service site x month of intake FEs. Reverse-sample instrument is computed as the share of cases handled by the case manager that ended up receiving Housing First assistance in all other case types. Standard errors are clustered at the case manager level. .

Appendix Table C.4. Biannual Estimates of the Effects of Housing First Assistance on Homelessness, Crime, and Health.

| Period: | Months 1-6 After Intake (1) | Months 7-12 After Intake (2) | Months 13-18 After Intake (3) | Months 19-24 After Intake (4) | Months 25-30 After Intake (5) |
|---|---|---|---|---|---|
| **A. Any Return to the Homeless System** | | | | | |
| RF: Housing First Placement Rate | -0.223 | -0.144 | -0.0993 | -0.0652 | -0.0540 |
| | (0.0623) | (0.0317) | (0.0328) | (0.0303) | (0.0325) |
| 2SLS: Housing First Placement | -0.263 | -0.170 | -0.117 | -0.0749 | -0.0667 |
| | (0.0667) | (0.0407) | (0.0394) | (0.0341) | (0.0377) |
| Dependent Mean | 0.29 | 0.18 | 0.15 | 0.13 | 0.12 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 12,982 | 8,947 |
| **B. Any Jail Booking** | | | | | |
| RF: Housing First Placement Rate | -0.0356 | -0.0608 | -0.00461 | -0.0405 | -0.0653 |
| | (0.0133) | (0.0200) | (0.0171) | (0.0165) | (0.0259) |
| 2SLS: Housing First Placement | -0.0433 | -0.0739 | -0.00561 | -0.0482 | -0.0875 |
| | (0.0158) | (0.0222) | (0.0207) | (0.0200) | (0.0338) |
| Dependent Mean | 0.05 | 0.05 | 0.04 | 0.03 | 0.02 |
| Number of Intake | 9,503 | 9,503 | 9,503 | 5,547 | 2,162 |
| **C. Any DHS Service** | | | | | |
| RF: Housing First Placement Rate | -0.0194 | -0.00938 | -0.00310 | -0.0387 | -0.0911 |
| | (0.0223) | (0.0238) | (0.0215) | (0.0290) | (0.200) |
| 2SLS: Housing First Placement | -0.0238 | -0.0115 | -0.00380 | -0.0432 | -0.126 |
| | (0.0278) | (0.0294) | (0.0264) | (0.0326) | (0.272) |
| Dependent Mean | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 |
| Number of Intakes | 7,401 | 7,401 | 7,401 | 4,034 | 451 |

*Notes:* Return to system includes any shelter stay, street outreach event, or a new intake. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.5. The Effect of Housing First Program Duration on Crime, Health, and Homelessness Outcomes.

| | Housing Stability and Homelessness Outcomes | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Return to Homeless System (1) | Emergency Shelter (2) | Street Outreach (3) | New Intake (4) | Continued Enrollment (5) | General Relief (6) |
| **A. Medium-Term (7-18 Months After Intake)** | | | | | | |
| 2SLS: Housing First Program Duration (1 = 365 days) | -0.353 | -0.154 | -0.136 | -0.133 | 0.808 | -0.104 |
| | (0.0794) | (0.0400) | (0.0709) | (0.0467) | (0.0548) | (0.0529) |
| Dependent Mean | 0.27 | 0.14 | 0.12 | 0.16 | 0.14 | 0.09 |
| Number of Cases | 15,353 | 15,353 | 15,353 | 15,353 | 15,353 | 9,771 |
| **B. Long-Term (19-30 Months After Intake)** | | | | | | |
| 2SLS: Housing First Program Duration (1 = 365 days) | -0.156 | -0.0632 | -0.0939 | -0.0672 | 0.174 | -0.176 |
| | (0.0634) | (0.0443) | (0.0517) | (0.0393) | (0.0563) | (0.0888) |
| Dependent Mean | 0.22 | 0.10 | 0.11 | 0.13 | 0.13 | 0.09 |
| Number of Cases | 8,947 | 8,947 | 8,947 | 8,947 | 8,947 | 2,398 |

| | Crime Outcomes | | | Health Outcomes | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Jail Booking | Criminal Charge | Probation | Any DHS | Any DMH | Any DPH |
| **C. Medium-Term (7-18 Months After Intake)** | | | | | | |
| 2SLS: Housing First Program Duration (1 = 365 days) | -0.0851 | -0.0621 | 0.00673 | -0.0107 | -0.00189 | -0.0571 |
| | (0.0282) | (0.0285) | (0.0195) | (0.0490) | (0.0281) | (0.0301) |
| Dependent Mean | 0.06 | 0.05 | 0.03 | 0.07 | 0.02 | 0.01 |
| Number of Cases | 9,503 | 9,503 | 9,771 | 7,401 | 9,742 | 4,376 |
| **D. Long-Term (19-30 Months After Intake)** | | | | | | |
| 2SLS: Housing First Program Duration (1 = 365 days) | -0.136 | -0.0749 | -0.0449 | -0.121 | 0.0482 | 0.0162 |
| | (0.0686) | (0.0471) | (0.0464) | (0.0749) | (0.0336) | (0.0372) |
| Dependent Mean | 0.05 | 0.04 | 0.02 | 0.05 | 0.01 | 0.00 |
| Number of Cases | 2,162 | 2,162 | 2,398 | 2,235 | 2,375 | 1,453 |

*Notes:* The estimates show the effect of an increase in duration of housing assistance by 365 days. Medium-term outcomes (panels A and C) are measured at 7-18 months after intake. Long-term outcomes (panels B and D) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake) and DPH (19-23 months after intake). Return to system includes any shelter stay, street outreach event, or a new intake. Continued enrollment is an indicator for enrollment in a rental subsidy (Housing First) program at any point between 7-18 (19-30) months after intake. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.6. Heterogeneous Effects of Housing First Assistance on Crime, Health, and Future Homelessness Outcomes.

| | **Gender** | | **Ethnicity and Race** | | | **Age** | | **Homeless History** | | **Jail History** | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample: | Males | Females | Blacks | Hispanics | Whites | Age $\leq$ 45 | Age > 45 | Chronic | Not-Chronic | Jail Hisotry | No Jail History |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| **A. Any Return to the Homeless System** | | | | | | | | | | | |
| **A.1. Medium-Term (7-18 Months after Intake)** | | | | | | | | | | | |
| 2SLS Estimate: Housing First Placement | -0.274 | -0.202 | -0.233 | -0.245 | -0.298 | -0.194 | -0.226 | -0.282 | -0.249 | -0.374 | -0.226 |
| (SE) | (0.0695) | (0.0657) | (0.0761) | (0.0810) | (0.137) | (0.0627) | (0.0904) | (0.0799) | (0.0865) | (0.161) | (0.0530) |
| Dependent Mean | 0.26 | 0.29 | 0.28 | 0.25 | 0.27 | 0.24 | 0.31 | 0.29 | 0.25 | 0.28 | 0.27 |
| Number of Intakes | 10,308 | 4,796 | 7,879 | 3,704 | 2,773 | 7,340 | 7,765 | 8,918 | 6,224 | 2,027 | 13,088 |
| **A.2. Long-Term (19-30 Months after Intake)** | | | | | | | | | | | |
| 2SLS Estimate: Housing First Placement | -0.155 | -0.252 | -0.123 | -0.163 | -0.310 | -0.164 | -0.153 | -0.166 | -0.0312 | -0.0593 | -0.119 |
| (SE) | (0.0831) | (0.118) | (0.101) | (0.105) | (0.175) | (0.107) | (0.106) | (0.0761) | (0.120) | (0.205) | (0.0618) |
| Dependent Mean | 0.22 | 0.22 | 0.22 | 0.21 | 0.22 | 0.20 | 0.23 | 0.23 | 0.20 | 0.23 | 0.22 |
| Number of Intakes | 5,888 | 2,910 | 4,837 | 1,930 | 1,589 | 3,912 | 4,869 | 5,407 | 3,420 | 1,135 | 7,670 |
| **B. Any Jail Booking** | | | | | | | | | | | |
| **B.1. Medium-Term (7-18 Months after Intake)** | | | | | | | | | | | |
| 2SLS Estimate: Housing First Placement | -0.0849 | -0.0299 | -0.0664 | 0.00295 | -0.0567 | -0.117 | -0.00772 | -0.0400 | -0.165 | -0.132 | -0.0242 |
| (SE) | (0.0338) | (0.0325) | (0.0391) | (0.0436) | (0.0396) | (0.0424) | (0.0411) | (0.0257) | (0.0558) | (0.157) | (0.0178) |
| Dependent Mean | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 | 0.07 | 0.07 | 0.06 | 0.33 | 0.02 |
| Number of Intakes | 6,245 | 3,105 | 5,081 | 2,106 | 1,699 | 4,205 | 5,135 | 5,727 | 3,652 | 1,230 | 8,126 |
| **B.2. Long-Term (19-30 Months after Intake)** | | | | | | | | | | | |
| 2SLS Estimate: Housing First Placement | -0.200 | 0.00253 | -0.122 | -0.107 | -0.388 | -0.154 | -0.0528 | -0.174 | 0.0241 | -0.280 | -0.0703 |
| (SE) | (0.112) | (0.0450) | (0.0765) | (0.0729) | (0.392) | (0.0952) | (0.0834) | (0.0811) | (0.107) | (0.600) | (0.0352) |
| Dependent Mean | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.23 | 0.02 |
| Number of Intakes | 1,412 | 711 | 1,156 | 424 | 428 | 903 | 1,221 | 1,347 | 780 | 265 | 1,868 |
| **C. Any DHS Service** | | | | | | | | | | | |
| **C.1. Medium-Term (7-18 Months after Intake)** | | | | | | | | | | | |
| 2SLS Estimate: Housing First Placement | 0.0516 | -0.0613 | -0.0690 | 0.125 | -0.0609 | -0.00359 | 0.0221 | -0.0296 | 0.0774 | -0.0259 | -0.0130 |
| (SE) | (0.0400) | (0.0604) | (0.0614) | (0.0708) | (0.0525) | (0.0421) | (0.0526) | (0.0406) | (0.119) | (0.169) | (0.0383) |
| Dependent Mean | 0.07 | 0.08 | 0.07 | 0.08 | 0.07 | 0.08 | 0.07 | 0.07 | 0.08 | 0.21 | 0.05 |
| Number of Intakes | 4,795 | 2,480 | 4,080 | 1,538 | 1,283 | 3,163 | 4,098 | 4,467 | 2,822 | 932 | 6,354 |
| **C.2. Long-Term (19-27 Months after Intake)** | | | | | | | | | | | |
| 2SLS Estimate: Housing First Placement | -0.188 | -0.0428 | -0.143 | 0.0535 | -0.604 | -0.0126 | -0.166 | -0.0981 | -0.165 | 0.0782 | -0.157 |
| (SE) | (0.0880) | (0.0938) | (0.105) | (0.123) | (0.341) | (0.0767) | (0.0882) | (0.0714) | (0.140) | (0.323) | (0.0757) |
| Dependent Mean | 0.05 | 0.05 | 0.04 | 0.05 | 0.06 | 0.05 | 0.05 | 0.05 | 0.05 | 0.10 | 0.04 |
| Number of Intakes | 1,465 | 725 | 1,192 | 442 | 438 | 930 | 1,271 | 1,396 | 811 | 277 | 1,925 |

*Notes:* The table presents IV estimates of the effect of Housing First program placement on various outcomes. Medium-term outcomes are measured at 7-18 months after intake. Long-term outcomes are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake). Each column describes the subsample used in the estimation. The outcome variable in panel A is any return to the homeless support system, including any shelter stay, street outreach event, or a new intake. The outcome variable in panel B is any jail booking by the Sheriff's department. The outcome variable in panel C is any Department of Health Services (DHS) service receipt, including emergnecy department visits and hospitalizations. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.7. IV Model with Three Treatment Options 'Long-Term Rental Subsidy', Short-Term Rental Subsidy', and 'No Rental Subsidy'.

| | **First Stages** | | **Reduced Form** | | | **IV** | | |
|---|---|---|---|---|---|---|---|---|
| Outcome: | Long-Term Rental Subsidy | Short-Term Rental Subsidy | Return to Homeless System | Any Jail Booking | Any DHS Service | Return to Home-less System | Any Jail Booking | Any DHS Service |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **A.. Medium-Term (7-18 Months after Intake)** | | | | | | | | |
| Long-Term Program Placement Rate | 0.591 | 0.0359 | -0.302 | -0.000712 | 0.0471 | | | |
| | (0.198) | (0.113) | (0.213) | (0.0700) | (0.106) | | | |
| Short-Term Program Placement Rate | -0.0192 | 0.871 | -0.192 | -0.0512 | -0.00783 | | | |
| | (0.0143) | (0.0591) | (0.0363) | (0.0167) | (0.0275) | | | |
| Long-Term Rental Subsidy | | | | | | -0.497 | 0.00115 | 0.0828 |
| | | | | | | (0.328) | (0.119) | (0.189) |
| Short-Term Rental Subsidy | | | | | | -0.232 | -0.0587 | -0.00403 |
| | | | | | | (0.0483) | (0.0206) | (0.0363) |
| SW F-stat (Instrument) | 13.35 | 166.71 | | | | | | |
| Dependent Mean | 0.01 | 0.05 | 0.27 | 0.06 | 0.07 | 0.27 | 0.06 | 0.07 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 9,503 | 7,401 | 15,353 | 9,503 | 7,401 |
| **B. Long-Term (19-30 Months after Intake)** | | | | | | | | |
| Long-Term Program Placement Rate | 0.575 | 0.0240 | -0.638 | -0.0957 | 0.116 | | | |
| | (0.184) | (0.132) | (0.156) | (0.0671) | (0.126) | | | |
| Short-Term Program Placement Rate | -0.0456 | 0.860 | -0.110 | -0.0975 | -0.130 | | | |
| | (0.0294) | (0.0823) | (0.0512) | (0.0310) | (0.0515) | | | |
| Long-Term Rental Subsidy | | | | | | -1.102 | -0.101 | 0.203 |
| | | | | | | (0.520) | (0.0992) | (0.212) |
| Short-Term Rental Subsidy | | | | | | -0.186 | -0.131 | -0.135 |
| | | | | | | (0.0705) | (0.0516) | (0.0690) |
| SW F-stat (Instrument) | 10.44 | 62.97 | | | | | | |
| Dependent Mean | 0.02 | 0.06 | | | | 0.22 | 0.05 | 0.05 |
| Number of Intakes | 8,947 | 8,947 | | | | 8,947 | 2,162 | 2,235 |

*Notes:* Medium-term outcomes (panel A) are measured at 7-18 months after intake. Long-term outcomes (panel B) are measured at 19-30 months after intake, with the exception of DHS (19-27 months after intake. Return to system includes any shelter stay, street outreach event, or a new intake. All specifications include site x month of intake FEs and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.8. Specification Checks - Minimum Number of Cases per Case Manager

| | | Cases Handled by Case Manager in Sample | | | |
|---|---|---|---|---|---|
| | Baseline (1) | $\geq$ 35 Cases (2) | $\geq$ 40 Cases (3) | $\geq$ 45 Cases (4) | $\geq$ 50 Cases (5) |
| **A. Housing First Assistance Receipt (First-Stage)** | | | | | |
| First Stage: Housing First Placement Rate | 0.847 | 0.853 | 0.819 | 0.678 | 0.682 |
| | (0.0631) | (0.0700) | (0.0917) | (0.0933) | (0.0943) |
| Dependent Mean | 0.07 | 0.06 | 0.06 | 0.05 | 0.05 |
| Number of Intakes | 15,353 | 14,473 | 13,555 | 12,960 | 12,572 |
| **B. Any Return to Homeless System (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.195 | -0.213 | -0.212 | -0.188 | -0.181 |
| | (0.0379) | (0.0414) | (0.0538) | (0.0625) | (0.0622) |
| IV: Housing First Placement | -0.230 | -0.250 | -0.258 | -0.278 | -0.265 |
| | (0.0490) | (0.0541) | (0.0756) | (0.108) | (0.106) |
| Dependent Mean | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 |
| Number of Intakes | 15,353 | 14,473 | 13,555 | 12,960 | 12,572 |
| **C. Any Jail Booking (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.0498 | -0.0561 | -0.0569 | -0.0536 | -0.0551 |
| | (0.0170) | (0.0193) | (0.0231) | (0.0308) | (0.0308) |
| IV: Housing First Placement | -0.0606 | -0.0660 | -0.0700 | -0.0904 | -0.0926 |
| | (0.0193) | (0.0213) | (0.0254) | (0.0483) | (0.0482) |
| Dependent Mean | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| Number of Intakes | 9,503 | 9,049 | 8,435 | 8,051 | 7,857 |
| **C. Any DHS Service (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.00610 | -0.00540 | 0.000216 | 0.00808 | 0.00494 |
| | (0.0277) | (0.0325) | (0.0349) | (0.0457) | (0.0457) |
| IV: Housing First Placement | -0.00749 | -0.00639 | 0.000263 | 0.0121 | 0.00741 |
| | (0.0341) | (0.0387) | (0.0424) | (0.0683) | (0.0683) |
| Dependent Mean | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| Number of Intakes | 7,401 | 7,047 | 6,525 | 6,223 | 6,075 |

*Notes:* All specifications include site x month of intake fixed effects and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.9. Specification Checks - Fixed Effects Selection.

| | | **Fixed Effects Selection** | | | |
|---|---|---|---|---|---|
| | Baseline | Site x Quarter | Site x Year | Organization x Month | SPA x Month |
| | (1) | (2) | (3) | (4) | (5) |
| **A. Housing First Assistance Receipt (First-Stage)** | | | | | |
| First Stage: Housing First Placement Rate | 0.847 | 0.855 | 0.854 | 0.906 | 0.968 |
| | (0.0631) | (0.0613) | (0.0618) | (0.0479) | (0.0211) |
| Dependent Mean | 0.07 | 0.07 | 0.07 | 0.06 | 0.07 |
| Number of Intakes | 15,353 | 15,881 | 16,116 | 16,659 | 16,757 |
| **B. Any Return to Homeless System (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.195 | -0.177 | -0.170 | -0.241 | -0.166 |
| | (0.0379) | (0.0361) | (0.0304) | (0.0322) | (0.0245) |
| IV: Housing First Placement | -0.230 | -0.208 | -0.199 | -0.266 | -0.172 |
| | (0.0490) | (0.0464) | (0.0371) | (0.0397) | (0.0257) |
| Dependent Mean | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 |
| Number of Intakes | 15,353 | 15,881 | 16,116 | 16,659 | 16,757 |
| **C. Any Jail Booking (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.0498 | -0.0493 | -0.0333 | -0.0346 | -0.0126 |
| | (0.0170) | (0.0170) | (0.0197) | (0.0133) | (0.0146) |
| IV: Housing First Placement | -0.0606 | -0.0600 | -0.0407 | -0.0385 | -0.0129 |
| | (0.0193) | (0.0195) | (0.0230) | (0.0146) | (0.0150) |
| Dependent Mean | 0.06 | 0.06 | 0.06 | 0.06 | 0.07 |
| Number of Intakes | 9,503 | 9,755 | 9,914 | 10,114 | 10,216 |
| **C. Any DHS Service (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.00610 | -0.00365 | -0.00566 | -0.0555 | -0.0324 |
| | (0.0277) | (0.0286) | (0.0295) | (0.0227) | (0.0171) |
| IV: Housing First Placement | -0.00749 | -0.00449 | -0.00702 | -0.0607 | -0.0326 |
| | (0.0341) | (0.0351) | (0.0366) | (0.0243) | (0.0172) |
| Dependent Mean | 0.07 | 0.08 | 0.07 | 0.07 | 0.08 |
| Number of Intakes | 7,401 | 7,625 | 7,760 | 7,916 | 8,024 |

*Notes:* All specifications include site x month of intake fixed effects and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.10. Specification Checks - Treatment Timing Definition.

| | | Treatment Definition: Received Housing First Assistance Within | | | |
|---|---|---|---|---|---|
| | Baseline | 1 Month | 3 Months | 12 Months | 18 Months |
| | (1) | (2) | (3) | (4) | (5) |
| **A. Housing First Assistance Receipt (First-Stage)** | | | | | |
| First Stage: Housing First Placement Rate | 0.847 | 0.909 | 0.860 | 0.835 | 0.828 |
| | (0.0631) | (0.0598) | (0.0626) | (0.0656) | (0.0656) |
| Dependent Mean | 0.07 | 0.04 | 0.05 | 0.08 | 0.08 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 15,353 | 15,353 |
| **B. Any Return to Homeless System (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.195 | -0.192 | -0.201 | -0.197 | -0.196 |
| | (0.0379) | (0.0370) | (0.0375) | (0.0390) | (0.0399) |
| IV: Housing First Placement | -0.230 | -0.211 | -0.234 | -0.236 | -0.237 |
| | (0.0490) | (0.0450) | (0.0489) | (0.0508) | (0.0522) |
| Dependent Mean | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 15,353 | 15,353 |
| **C. Any Jail Booking (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.0498 | -0.0575 | -0.0506 | -0.0455 | -0.0433 |
| | (0.0170) | (0.0166) | (0.0165) | (0.0169) | (0.0166) |
| IV: Housing First Placement | -0.0606 | -0.0649 | -0.0611 | -0.0563 | -0.0545 |
| | (0.0193) | (0.0179) | (0.0189) | (0.0197) | (0.0195) |
| Dependent Mean | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| Number of Intakes | 9,503 | 9,503 | 9,503 | 9,503 | 9,503 |
| **C. Any DHS Service (Medium-Term)** | | | | | |
| RF: Housing First Placement Rate | -0.00610 | -0.00458 | 0.00335 | -0.00394 | -0.00271 |
| | (0.0277) | (0.0275) | (0.0268) | (0.0275) | (0.0283) |
| IV: Housing First Placement | -0.00749 | -0.00516 | 0.00407 | -0.00488 | -0.00341 |
| | (0.0341) | (0.0310) | (0.0325) | (0.0342) | (0.0358) |
| Dependent Mean | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| Number of Intakes | 7,401 | 7,401 | 7,401 | 7,401 | 7,401 |

*Notes:* All specifications include site x month of intake fixed effects and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

## Appendix Table C.11. Specification Checks -Instrument Definition.

| | Baseline | Instrument Type: Winsorized Instrument | Split Sample | Any Placement Rate |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **A. Housing First Assistance Receipt (First-Stage)** | | | | |
| First Stage: Housing First Placement Rate | 0.847 | 0.909 | 0.953 | 0.348 |
| | (0.0631) | (0.231) | (0.0792) | (0.105) |
| Dependent Mean | 0.07 | 0.07 | 0.05 | 0.07 |
| Number of Intakes | 15,353 | 15,353 | 7,546 | 15,353 |
| **B. Any Return to Homeless System (Medium-Term)** | | | | |
| RF: Housing First Placement Rate | -0.195 | -0.308 | -0.235 | -0.0902 |
| | (0.0379) | (0.119) | (0.0513) | (0.0324) |
| IV: Housing First Placement | -0.230 | -0.339 | -0.231 | -0.259 |
| | (0.0490) | (0.137) | (0.0498) | (0.0878) |
| Dependent Mean | 0.27 | 0.27 | 0.27 | 0.27 |
| Number of Intakes | 15,353 | 15,353 | 7,545 | 15,353 |
| **C. Any Jail Booking (Medium-Term)** | | | | |
| RF: Housing First Placement Rate | -0.0498 | -0.0517 | -0.0414 | -0.0155 |
| | (0.0170) | (0.0474) | (0.0292) | (0.0149) |
| IV: Housing First Placement | -0.0606 | -0.0638 | -0.0403 | -0.0397 |
| | (0.0193) | (0.0551) | (0.0275) | (0.0355) |
| Dependent Mean | 0.06 | 0.06 | 0.06 | 0.06 |
| Number of Intakes | 9,503 | 9,503 | 4,694 | 9,503 |
| **C. Any DHS Service (Medium-Term)** | | | | |
| RF: Housing First Placement Rate | -0.00610 | -0.0000028 | 0.00897 | -0.0303 |
| | (0.0277) | (0.0825) | (0.0479) | (0.0244) |
| IV: Housing First Placement | -0.00749 | -0.0000034 | 0.00853 | -0.0798 |
| | (0.0341) | (0.102) | (0.0454) | (0.0745) |
| Dependent Mean | 0.07 | 0.07 | 0.07 | 0.07 |
| Number of Intakes | 7,401 | 3,621 | 3,665 | 7,401 |

*Notes:* All specifications include site x month of intake fixed effects and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.12. Controlling for Case Manager Rates in Treatment Margins other than Housing First Assistance.

| | First Stage | Reduced Form | | | IV | | |
|---|---|---|---|---|---|---|---|
| Outcome: | Housing First Assistance | Return to Homeless System | Any Jail Booking | Any DHS Service | Return to Homeless System | Any Jail Booking | Any DHS Service |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **A. Baseline Specification** | | | | | | | |
| Housing First Placement Rate | 0.847 | -0.195 | -0.0498 | -0.00610 | | | |
| | (0.0631) | (0.0379) | (0.0170) | (0.0277) | | | |
| Housing First Placement | | | | | -0.230 | -0.0606 | -0.00749 |
| | | | | | (0.0490) | (0.0193) | (0.0341) |
| F-stat (Instrument) | 180.52 | | | | | | |
| **B. Control for Emergency Housing Placement Rate** | | | | | | | |
| Housing First Placement Rate | 0.846 | -0.203 | -0.0499 | -0.0179 | | | |
| | (0.0638) | (0.0380) | (0.0177) | (0.0288) | | | |
| Housing First Placement | | | | | -0.239 | -0.0601 | -0.0218 |
| | | | | | (0.0493) | (0.0200) | (0.0356) |
| F-stat (Instrument) | 175.83 | | | | | | |
| **C. Control for Emergency Housing and Non-Housing Services Placement Rates** | | | | | | | |
| Housing First Placement Rate | 0.824 | -0.210 | -0.0804 | -0.0153 | | | |
| | (0.0693) | (0.0407) | (0.0180) | (0.0312) | | | |
| Housing First Placement | | | | | -0.254 | -0.0976 | -0.0193 |
| | | | | | (0.0547) | (0.0217) | (0.0397) |
| F-stat (Instrument) | 141.39 | | | | | | |
| Dependent Mean | 0.07 | 0.27 | 0.06 | 0.07 | 0.27 | 0.06 | 0.07 |
| Number of Intakes | 15,353 | 15,353 | 9,503 | 7,401 | 15,353 | 9,503 | 7,401 |

*Notes:* All specifications include site x month of intake fixed effects and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

Appendix Table C.13. IV Model with Four Treatment Options 'Housing First', 'Emergency Housing', 'Non-Housing Services' and 'No Assistance'.

| | **First Stages** | | | **Reduced Form** | | | **IV** | | |
|---|---|---|---|---|---|---|---|---|---|
| Sample: | Housing First | Emergency Housing | Non-Housing Program | Return to Homeless System | Any Jail Booking | Any DHS Service | Return to Homeless System | Any Jail Booking | Any DHS Service |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **A.1. Medium-Term (7-18 Months after Intake)** | | | | | | | | | |
| Housing First Placement Rate | 0.824 | -0.0745 | -0.0458 | -0.210 | -0.0804 | -0.0153 | | | |
| | (0.0693) | (0.0480) | (0.0507) | (0.0407) | (0.0180) | (0.0312) | | | |
| Emergency Housing Placement Rate | -0.0205 | 0.838 | -0.177 | -0.0338 | -0.0249 | -0.0370 | | | |
| | (0.0308) | (0.0408) | (0.0741) | (0.0410) | (0.0185) | (0.0342) | | | |
| Non-Housing Services Placement Rate | -0.0389 | -0.0800 | 0.639 | -0.0124 | -0.0693 | 0.00706 | | | |
| | (0.0715) | (0.0347) | (0.104) | (0.0412) | (0.0230) | (0.0339) | | | |
| Housing First Program Assistance | | | | | | | -0.262 | -0.103 | -0.0240 |
| | | | | | | | (0.0588) | (0.0221) | (0.0399) |
| Emergency Housing Program Assistance | | | | | | | -0.0556 | -0.0566 | -0.0455 |
| | | | | | | | (0.0644) | (0.0324) | (0.0497) |
| Non-Housing Services Program Assistance | | | | | | | -0.0423 | -0.104 | -0.000109 |
| | | | | | | | (0.0781) | (0.0350) | (0.0491) |
| SW F-stat (Instrument) | 191.74 | 83.61 | 64.23 | | | | | | |
| Dependent Mean | 0.07 | 0.36 | 0.27 | 0.27 | 0.06 | 0.06 | 0.27 | 0.06 | 0.06 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 15,353 | 9,503 | 9,503 | 15,353 | 9,503 | 9,503 |

*Notes:* All specifications include site x month of intake fixed effects and all the controls listed in Table 3. Standard errors are clustered at the case manager level.

# D Cost-Benefit Analysis Details

To calculate the costs of Housing First programs reported in Table D.1, I multiply the number of housing assistance days received for each individual in the sample during the 18-month or 30-month period after intake by the average cost per day of each program type, such that direct housing costs are set $40 per day for rapid re-housing, and $50 per day for permanent supportive housing (Los Angeles Homelessness Services Authority, 2017). The IV estimate, which uses this outcome, measures a cost of $9,366 per Housing First program enrollment in the medium-term and $11,010 in the long-term.[49]

On the benefits side, I measure three broad categories. First, there is a reduction in homeless support system spending on emergency shelter stays and future housing assistance due to fewer returns to the homeless support system. For emergency shelter days, I estimate savings of $1,500 per Housing First program enrollment, both in the medium- and long-term. Next, I compute the savings in housing costs per homeless system return avoided as the average housing assistance cost of an assessment in the sample. Homeless support system average savings in housing assistance costs are estimated to be $4,000 per intake. I then create an outcome variable that takes the total number of returns to the homeless support system in the 18- and the 30 months after intake multiplied by $4,000. Using this measure, I estimate savings of $3,249 and $5,234 in the medium- and long-term per Housing First program enrollment, respectively.

The second and third categories of benefits I compute are related to the utilization of public health and services and interaction with law enforcement agencies. 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

[49] This measure captures the average cost of Housing First programs and not the marginal cost, which I would ideally estimate.

treatments or occurrences of each type of service. The IV estimates of these savings are \$761 and -\$1,347 for health costs and \$478 and \$3,575 for law enforcement costs in the medium- and long-term, respectively. programs.

The third category of benefits is due to increased employment and reduction in social benefits receipt that I find in Section 5. I estimate the increase in taxes minus social benefits to be \$1,515 and \$2,948 in the medium- and long-term per Housing First program enrollment, respectively.

Overall, I find that the savings offset a substantial portion of Housing First program costs to public agencies in both the 18 and 30 months following intake. I note that these savings are likely to be even more significant, as I ignore the indirect benefits of reducing 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, in Panels A.2 and B.2, I break Housing First programs by type (short- and long-term rental subsidy programs) and estimate the cost of each using the two instruments I used when estimating the impact of short- versus long-term rental subsidy housing programs in Section 5.3. I find that the savings are substantial in both rapid re-housing and permanent supportive housing programs but pay off faster for rapid re-housing programs.

Appendix Table D.1. The Costs and Benefits of Housing First Assistance for the Homeless.

| | Costs | Benefits - Public Agencies Expenditures | | | | | Benefits - Overall Expenditures | |
|---|---|---|---|---|---|---|---|---|
| | | Homeless Support System | | Other Public Agencies | | Self Sufficiency | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dependent Variable: | Days in Housing Programs | Emergency Shelter Days | Future Returns to Homeless System | Health | Law Enforcement | Taxes Paid Minus Public Benefits | Without Self Sufficiency | With Self Sufficiency |
| **A. Medium-Term (1-18 Months After Intake)** | | | | | | | | |
| **A.1. Housing Assistance - All Types** | | | | | | | | |
| IV: Housing Assistance | 9,617 | -1,448 | -3,249 | -761.4 | -477.5 | -1,515 | -5,484 | -10,810 |
| | (1,148) | (367.2) | (572.5) | (968.3) | (381.0) | (361.8) | (1,160) | (2,126) |
| **A.2. Housing Assistance - By Type** | | | | | | | | |
| IV: Long-Term Rental Subsidy (PSH) | 20,387 | -4,342 | -7,964 | 662.4 | 2,693 | 555.0 | -6,129 | -24,682 |
| | (2,951) | (3,099) | (3,460) | (6,080) | (4,152) | (1,261) | (6,914) | (17,000) |
| IV: Short-Term Rental Subsidy (RRH) | 9,708 | -1,472 | -3,289 | -706.9 | -381.6 | -1,431 | -5,508 | -12,483 |
| | (1,070) | (368.1) | (560.4) | (1,044) | (474.6) | (382.7) | (1,259) | (3,684) |
| Dependent mean | 1,707 | 1,466 | 3,492 | 1,201 | 861 | 45 | 6,387 | 10,173 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 7,401 | 9,503 | 5,709 | 7,401 | 2,987 |
| **B. Long-Term (1-30 Months After Intake)** | | | | | | | | |
| **B.1. Housing Assistance - All Types** | | | | | | | | |
| IV: Housing Assistance | 11,010 | -1,523 | -5,234 | 1,347 | -3,575 | -2,948 | -14,885 | -36,317 |
| | (1,696) | (437.4) | (1,037) | (2,399) | (1,205) | (680.0) | (3,209) | (10,442) |
| **B.2. Housing Assistance - By Type** | | | | | | | | |
| IV: Long-Term Rental Subsidy (PSH) | 32,520 | -5,589 | -18,217 | 5,321 | -4,687 | -459.6 | -10,289 | -46,081 |
| | (5,890) | (3,646) | (6,965) | (6,336) | (2,959) | (2,448) | (10,167) | (27,029) |
| IV: Short-Term Rental Subsidy (RRH) | 11,190 | -1,557 | -5,343 | 1,219 | -3,539 | -2,847 | -15,034 | -37,073 |
| | (1,542) | (442.4) | (982.9) | (2,253) | (1,201) | (709.1) | (3,081) | (11,246) |
| Dependent mean | 2,724 | 1,794 | 6,394 | 1,516 | 1,273 | -327 | 11,911 | 18,074 |
| Number of Intakes | 15,353 | 15,353 | 15,353 | 2,235 | 2,162 | 5,709 | 2,162 | 971 |

*Notes:* Estimation sample and specification with all controls. Standard errors are clustered at the case manager 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. Self sufficiency savings 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 savings are the sum of columns 2-5 (without self-sufficiency) and columns 2-6 (with self sufficiency). Costs and benefits are estimated for an 18-month period in panel A and for 30-month period in panel B. .