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Evaluating Los Angeles Homelessness Policy Using System Dynamics Modeling

By

Dandan Kowarsch

Claremont Graduate University

2022

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Dandan Kowarsch as fulfilling the scope and quality requirements for meriting the degree of Doctor of International Politics & Political Science.

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DEDICATION

Dedicated to my parents, Shu Yang and Wanxia Wang.

Abstract

Los Angeles Homelessness Policy Evaluation Using System Dynamics Simulation

By

Dandan Kowarsch

Claremont Graduate University: 2022

The aim of this dissertation is to advocate policies that can effectively address the challenge of unsheltered homelessness. Using a case study of Los Angeles homelessness, I evaluated policies aimed at easing homelessness using scenario analysis, employing system dynamic (SD) modeling. This study primarily focuses on the evaluation of the Housing First approach and the identification of more effective responses to homelessness.

I use a linear regression model to identify key prevention policy levers, including, but not limited to, limits on eviction moratorium, rent stabilization, and affordable housing. Drawing on the information gathered from the regression, the SD model is able to capture the impact of the key factors on homelessness prevention. Combined with the housing sub-systems, the SD model can simulate the behavior of the homeless population under different policy arrangements. The evidence drawn from the statistical model as well as the SD model suggests that when long-term and short-term housing programs are compared, long-term housing programs, such as the permanent supportive housing (PSH) approach, better meet the needs of chronically and mentally ill homeless people in Los Angeles, though they are more costly than short-term housing approaches.

In order to mitigate homelessness, the City and County of Los Angeles should:

(1) Adopt a homelessness prevention plan that can constrain growth in the number of people evicted from rental units and the number of people discharged from jails and foster families.

(2) Continue to employ the PSH approach as its primary means of combating homelessness.

(3) Help recipients of long-term support become self-sufficient in order to reduce the cumulative financial burden created by the operation of long-term support programs for homeless people.

The SD simulation model results suggest that, if Los Angeles tripled total funding for PSH programs, without adopting any short-term housing approaches, the unsheltered homeless population would likely fall below five hundred by 2030.

Acknowledgements

I sincerely appreciate the advice given by Alexander Gittinger, the Homeless Solution Manager of the City of Malibu. He deserves tremendous credit for his assistance in reviewing the system dynamics model and my first homeless research paper.

I thank the Homeless Solution Manager and his team from the City of Riverside for the opportunity they provided me to interview homeless people in the City of Riverside, and for the valuable insights about the characteristics of the homeless.

Many thanks to Dr. Heather Campbell. I am inspired by Dr. Campbell's rigorous attitude of seeking academic excellence.

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Introduction

1 A Brief Introduction to Homelessness in Los Angeles

Some theories argue that “the eco-social system” is responsible for homelessness, others that homeless individuals are primarily responsible for their circumstances. More than half of those becoming homeless in 2021 cited economic hardships, likely resulting from a challenging job market, as responsible for their lack of housing, especially highlighting a shortage of affordable housing (LAHSA, 2020a). Policy makers sharing this perspective have supported policies addressing housing options, notably so-called Housing First policy solutions (Los Angeles Times Editorial Board, 2021). In 2016, the City of Los Angeles approved the $1.2 billion Homelessness Reduction and Prevention, Housing and Facilities Bond, intended to triple L.A.'s annual production of affordable, temporary, and supportive housing (Itchon, 2022).

The City and County of Los Angeles have been endeavoring to increase the supply of supportive housing, with an emphasize on the expansion of short-term housing since 2013 because policy makers believed the short-term housing would be less expensive than permanent supportive housing (PSH). Unlike PSH, the rapid re-housing program is designed as a short-term bridge that will allow people to move quickly out of the streets and back to normal lives (Cunningham et al., 2018). Services provided by the rapid program are time limited, however. While the limitation of the services provided under the program reduces up-front costs, it also creates anxiety among participants regarding their uncertain future (Fisher et al., 2014). Many participants fail, or are concerned that they may fail, to secure stable employment within a short period of time (Kowarsch and Yang, 2021), and may thus become homeless again after exiting the program.

While the total homeless population in the U.S. is decreasing (HUD, 2019), the homeless population in Los Angeles is rising. Homelessness, particularly unsheltered homelessness, is a challenge not only to the City of Los Angeles, but also San Francisco, Portland, and Seattle. By contrast, cities on the East coast, such as New York and Washington, DC, host an even larger percentage of sheltered homeless people that the cities on the West coast . Policy makers and analysts continue to assess the effectiveness of alternative responses. Rent subsidies are widely available and have proven helpful in moving people off the streets after they find themselves among the unsheltered homeless because of sudden financial difficulties. For instance, a rapid re-housing program using vouchers to subsidize homeless people's rent payments might be effective in handling unsheltered homeless people in need of temporary support. By contrast, this and other means of short-term support for housing will not prove effective in the case of people who need long-term housing and health support for reasons not limited to financial insecurity.

Short-term housing approaches may reduce the number of unsheltered homeless people, an effective homelessness prevention strategy can play a critical role in reducing the total number of homeless people by reducing the likelihood that people will become homeless in the first place. In addition to chronic homelessness, an integrated, long-term housing program, complemented by ongoing health and social support, can respond effectively to the needs of those who are homeless periodically or chronically, serving in this way as a primary driver of homelessness mitigation.

2 An Introduction to the Research Design and Outline of the Study

To understand the intertwined relationship among programs offering housing and other kinds of support to homeless people, as well as various homelessness prevention strategies, I use a regression model to estimate the effectiveness of approaches to homelessness prevention. Then, I use the indicators identified as significant in light of the regression for parameter calibration, focusing on the homelessness prevention level and using an SD model. I use econometric analyses to identify key factors relevant to homelessness prevention; I also use the SD simulation model to reveal endogenous and causal relationship between housing and homelessness. The implementation of the SD model also overcomes data issues related to the supportive housing programs and homeless population in Los Angeles. Moreover, the complete SD model—which comprises subsystems concerned with homelessness prevention, short-term housing programs, and PSH—is validated and used to predict the homeless populations likely to result from different strategies. This model thus allows us to evaluate the impact of the changes in various policy levers related to the various subsystems on the overall homeless population. Figure 1-1 illustrates the process of the research design.

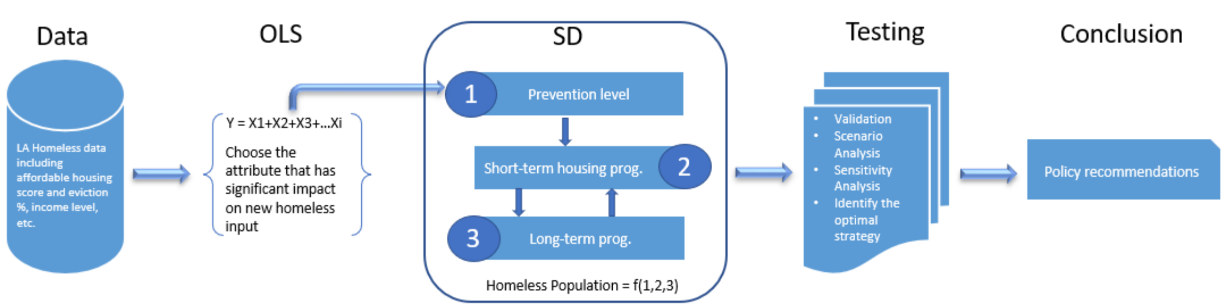


Figure 1. Research Design

In this study, I proceed as follows. I begin with a brief introduction, explaining both the problem and the theoretical approach I take as I seek to illuminate it. I consider the background to the problem in some detail in Chapter 1, offering interpretations of the federal definitions of homelessness, relevant regulations, and grants facilitating the delivery of supportive programs for homeless people. I also consider major stakeholders and compare the benefits of the short-term and long-term housing approaches. In Chapter 2, I review some relevant contemporary literature regarding homelessness in general and homelessness in Los Angeles in particular. In Chapter 3, I introduce the SD model's architecture, initialization, validation, and prediction results, focusing on the period from 2020 to 2030. Exploring the concurrent causes for homelessness. In Chapter 4 I elaborate the SD model's behavior evaluation using scenario analysis, sensitivity analysis, and equilibrium analysis. I summarize key policy implementations in Chapter 5 before considering potential weaknesses of my research approach and suggesting avenues for further investigation in Chapter 6.

Particularly in Chapter 4, I use scenario analysis to assess following factors, on the assumption of sufficient funding for homelessness services: (1) the impact of short-term housing on overall unsheltered homelessness under the various circumstances of housing inventory capacity, the program's duration, and the ratio of the returning homeless population; (2) the impact of long-term housing and services on unsheltered homelessness under the various circumstances of housing inventory capacity and the program's duration; and (3) the impact of services without housing assistance on unsheltered homelessness. I use sensitivity analysis to identify the structure and macro-level behavior of the system responsible for the level of homelessness. I do so by observing and evaluating phase portraits plots to discern the potential drivers of homelessness.

The central objective of this study is to evaluate contemporary Los Angeles homelessness policies and to identify the most effective policies and implementation strategies by mimicking the real-world problem using an SD model. Featuring stocks and flows connected by feedback loops and delays, the SD approach makes it possible to evaluate various possible effects on Los Angeles homelessness in the context of the region's social-economic environment.

Chapter 1
Background

1.1 Housing First Policy to Ease Homelessness

Los Angeles has had considerable difficulty with homeless population for years. The combination of warm weather and economical decline lead to the increase in unsheltered homeless (Clifasefi et al., 2016; Corinth, 2017; Fowler et al., 2018). The total unsheltered homeless in Los Angeles City and County was over 46,000 on a single night in January of 2020. In the same year, the homeless population in Los Angeles County was 66,436, approximately 12.7 percent increases (LAHSA 2020b). The 2020 pandemic is likely to lead a higher increase in homeless population since the pandemic shock tends to create greater negative effect on vulnerable populations, including but not limited to, low-income people, people with disability, new immigrants with low skills, and those who don't have any social ties with their relatives and friends and also cannot be self-sufficient.

Currently, Housing First policy (HF) has been prioritized as the dominant strategy to fight against homelessness nationwide (Perl, 2017; The Council of Economic Advisers, 2019). According to HUD's Housing First in Permanent Supportive Housing Briefing, the HF approach provides homes to individuals and families who are experiencing homelessness without preconditions and barriers to entry, such as sobriety, treatment, or service participation requirements. The Housing First policy was thought to be helpful in reducing homelessness because first it is inclusive in terms of taking care of not only homeless families but also homeless individuals. Second, it is expected to be a "fast assistant", meaning that when someone becomes homeless, he or she is expected to be served as soon as possible. Third, the Housing First approach is expected to be an integrated strategy which combines housing and supportive services.

While the nation's homeless population has decreased after 2007, the homeless population is raising in Los Angeles (HUD, 2019). Housing First policy seems to be ineffective in battling Los Angeles homelessness as the empirical evidence suggests that Los Angeles homeless population and Federal supportive housing programs are positively associated with one another (Kowarsch & Yang, 2021). To explore cascade causes, the homeless housing strategies should be recapped in a broader array. In this study, the evaluation of homeless policy focuses on preventative programs, short-term housing, and long-term housing programs. In general, there are four major types of solutions for homeless people: emergency shelter (ES), transitional housing (TH) for chronically individual homeless, the rapid re-housing (RRH) for individual homeless, and the permanent supportive housing (PSH) for chronically family-based or mentally or physically disabled individual-based homeless people (Perl, 2017). The RRH and PSH are two important components of Housing First approach. The rapid re-housing which is prioritized over other housing programs in Los Angeles is questionable. The rapid re-housing is about a 3 to 9-month temporary housing support for individual homeless who are not qualified for neither shelter nor permanent supportive housing (Perl, 2017; The Council of Economic Advisers, 2019). The problem, however, is that when the homeless are assigned into the RRH program, they are not counted as the homeless (Perl, 2017, The Council of Economic Advisers, 2019). Since some of those who are in the RRH program cannot be self-sufficient in such a short period of time, if the program is terminated, without continuous supports, the homeless people are more likely to return to the streets.

It is unclear that whether Los Angeles City and County should focus on a top-down approach, including housing support and living subsidize, or bottom-up approach, such as mental health service and educational training, to combat homelessness. What Los Angeles has been implementing primarily is the structural level assistance. Emergency shelters (ES), Rapid Re-housing Program (RRH), Transitional Housing Program (TH), and Permanent supportive Housing Programs (PSH) are the typical tactics used for easing homelessness in Los Angeles. The various housing supports seem to be ineffective as the overall homeless population has been growing since 2012. Figure 1-1-1 illustrates Los Angeles homeless population growth trend between 2007 and 2020.

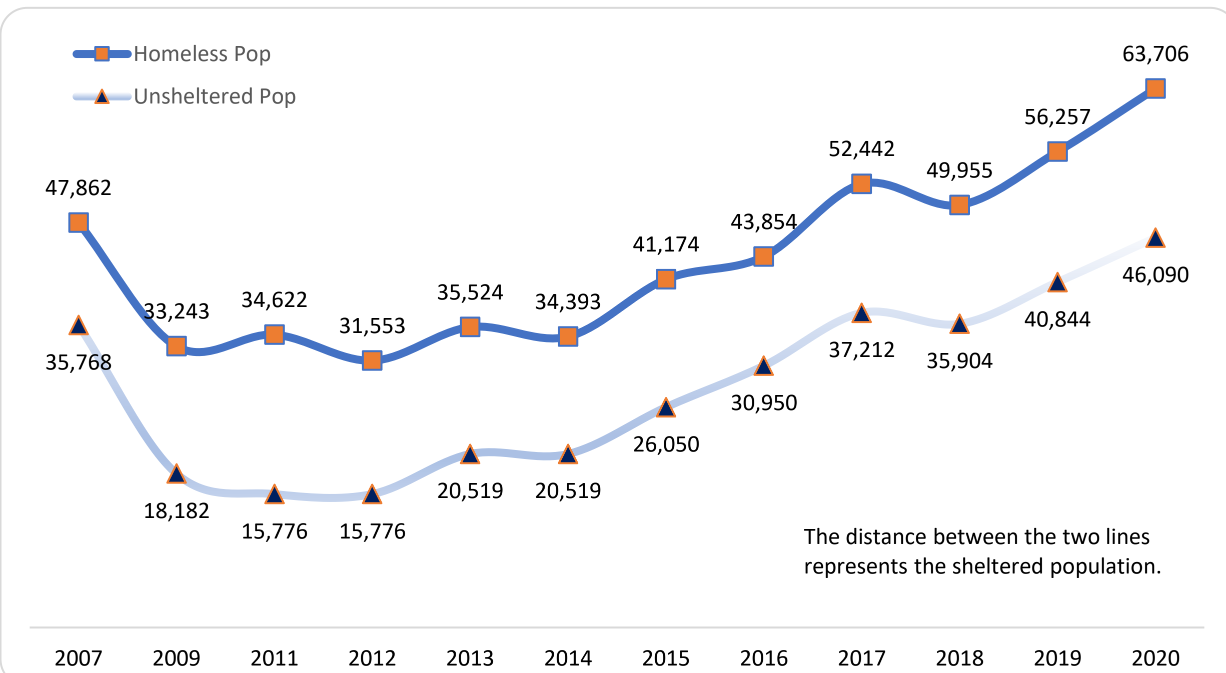


Figure 1-1-1. Los Angeles Homeless Population Trend

The homeless population includes the total sheltered homeless and the homeless people in the transitional housing programs. The gap between the homeless population (upper dark blue line) and the unsheltered homeless population (bottom light blue line) projects the population who are in the emergency shelters and the transitional housing programs.

Note that in Figure 1-1-1, the Los Angeles unsheltered homelessness head counts data covers 2007 through 2020. Between 2009 and 2014, the reported homeless head counts of 2009 and 2010 are identical, the reported homeless head counts of 2011 and 2012 are the same, and the reported homeless head counts of 2013 and 2014 are not different. This invariance would create a potential threat for a regression modeling approach when the sample size is small. Figure 1-1-2 below depicts the changes of the bed inventory in primary housing programs.

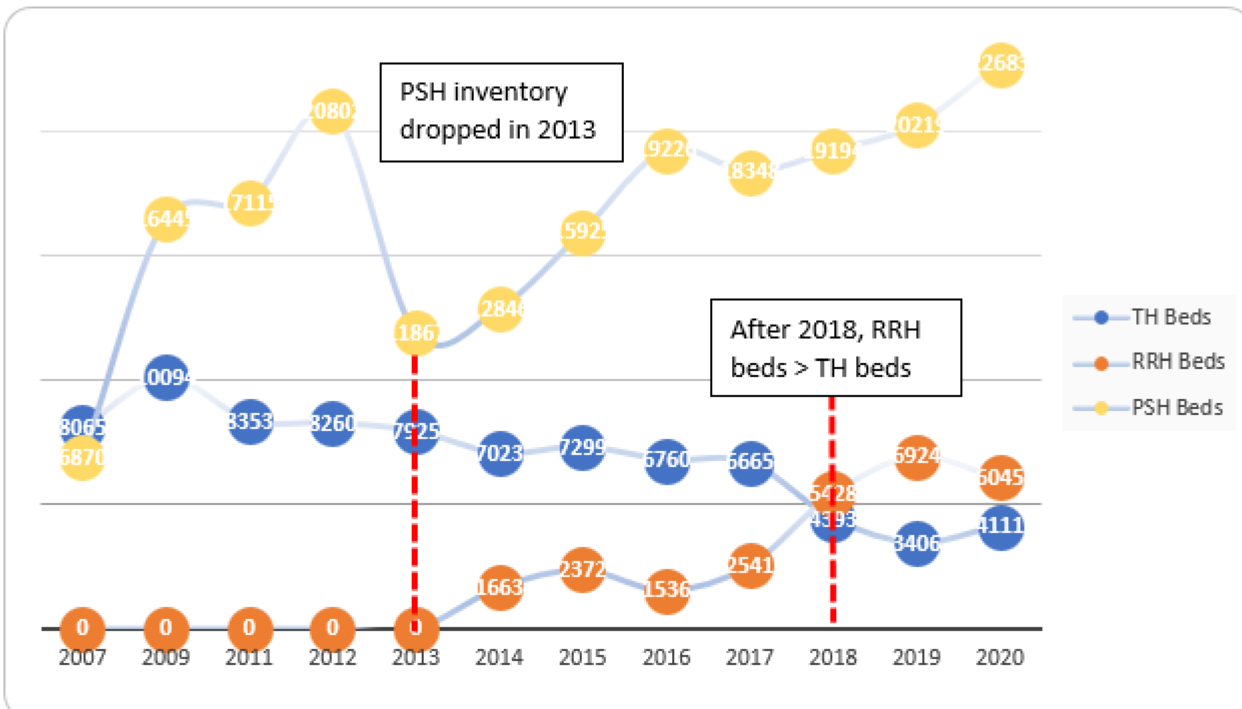


Figure 1-1-2. Los Angeles Bed Inventory in Various Housing Programs

Among those housing programs, the top line reflects the PSH bed inventory trend between 2007 and 2020, the middle line reflects the TH bed inventory trend and the bottom-line projects the RRH bed inventory trend from 2007 to 2020.

Note that the PSH bed inventory dropped significantly in 2013, from 20,802 in 2012 down to 11,867 in 2013 while the RRH has grown since 2013. In 2018, there were more RRH beds than the TH beds, which indicates there must be a decrease in unsheltered homeless population in 2018 because those who used RRH were not counted as the homeless. The relationship between the PSH beds and unsheltered homelessness is depicted in Figure 1-1-3.

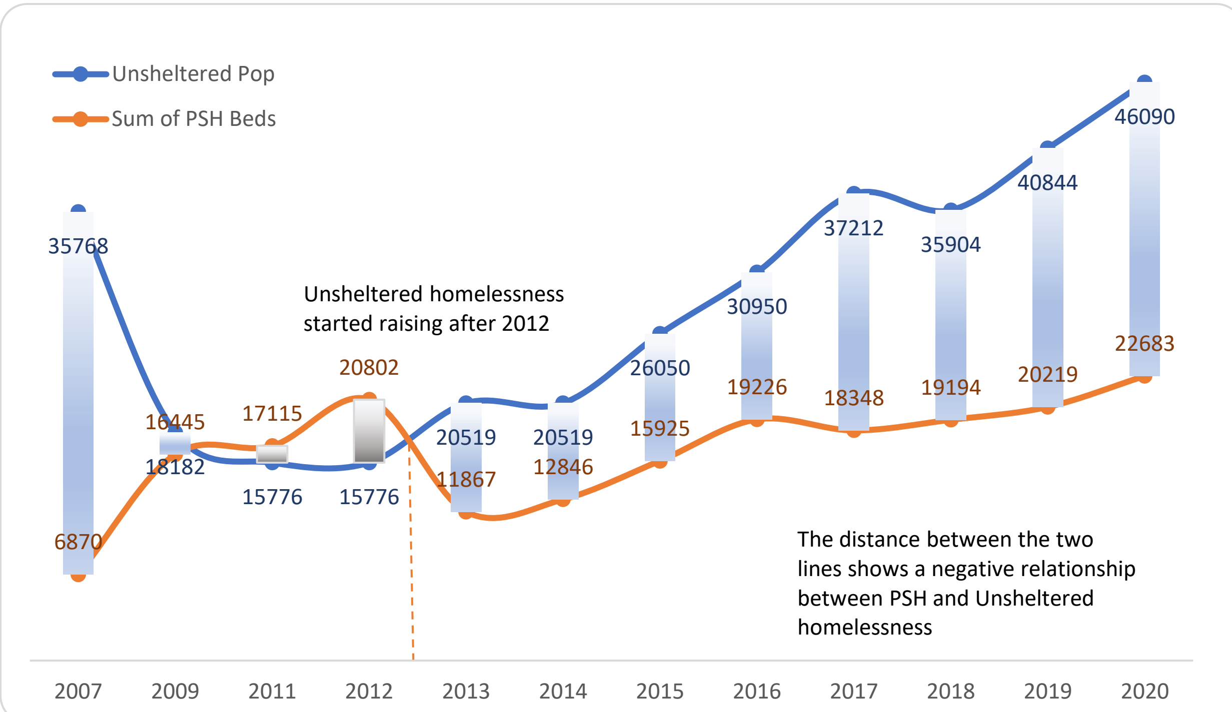


Figure 1-1-3. Unsheltered Homeless Population vs. the Permanent Supportive Housing Inventory

Comparing the historical data points showing in Figure 1-1-3, we can assume a negative liner relationship between the PSH and unsheltered homelessness. As the PSH increases between 2011 and 2012, the unsheltered homelessness dropped. Moreover, after the large reduction in the PSH bed inventory in 2013, its long-term impact on homelessness is observed as a continuing growth in unsheltered homeless population between 2013 and 2020.

The descriptive analysis mentioned above, however, has limited inferential power. In Chapter 5, the system dynamics model as prescriptive analysis will be discussed in depth for forecasting Los Angeles unsheltered homeless population based on causal relationships between variable of interests and unsheltered homeless population.

1.2 Homelessness Definition

Reasons contributing to homelessness have been studied for many years. Some argue that city's gentrification process results in homelessness. Some assert that the reduced need for unskilled labor has a positive impact on homelessness. Others claim that the declined family ties that allow relatives to accommodate homeless family member, or the decreased value of public benefits, or changed admissions standards at mental hospitals can also affect homelessness. Who are defined as the homeless? According to Homeless Emergency Assistance and Rapid Transition to Housing Act (HEARTH) (HUD EXCHANGE, 2009), "homeless individual" was defined in Section 103(a) of the McKinney-Vento Act [1]

> *"(1) an individual who lacks a fixed, regular, and adequate nighttime residence; and*
> *(2) an individual who has a primary nighttime residence that is – (A) a supervised publicly or privately operated shelter designed to provide temporary living accommodations (including welfare hotels, congregate shelters, and transitional housing for the mentally ill); (B) an institution that provides a temporary residence for individuals intended to be institutionalized; or (C) a public or private place not designed for, or ordinarily used as, a regular sleeping accommodation for human beings."*

[1] https://www.hud.gov/sites/documents/HAAA_HEARTH.PDF

The HEARTH Act, which took effect on January 4, 2012, expanded the definition of "homeless individuals" to those who face housing instability as a form of homelessness. The Act added that those living in hotels or motels paid by a government entity or charitable organization are considered homeless. The amended law also added locations that were not considered suitable places for people to sleep, including cars, parks, abandoned buildings, bus or train stations, airports, and campgrounds. When HUD issued its final regulation in December 2011, it clarified that a person exiting an institution cannot have been residing there for more than 90 days and still be considered homeless. The time frame in the homeless definition creates tensions for the institutions where the homeless temporarily stay. For the legal department, the detained homeless must be released within 90 days, otherwise they cannot be considered homeless if they stay in prison for longer than 90 days (HUD EXCHANGE, 2009).

Compared to adult homeless, youth homeless is defined as those who are under the age of 25, living in a private or publicly operated temporary living facility or in transitional housing (HUD EXCHANGE, 2009). Families who are defined as homeless must meet the requirement of having experienced at least 60 days without living independently in permanent housing. The youth or families with children can be expected to continue in unstable housing due to factors such as chronic disabilities, chronic physical health or mental health conditions, substance addiction, histories of domestic violence or childhood abuse, the presence of a child or youth with a disability, or multiple barriers to employment.

To know who are the homeless, in general, it is preferred that service providers have third party documentation that an individual or family is homeless, such as an eviction order verification from a family member with whom a homeless individual or family had lived. But under some circumstances, it may also be acceptable to confirm homelessness based on intake worker observation or certification from the person or head of household who is homeless. While someone is seeking assistance at an emergency shelter, through a street outreach program, or from a victim service provider, failure to separately verify homeless status should not prevent an individual or family from receiving immediate assistance. This regulation is helpful for those who face unexpected hardship, and the immediate housing assistance is just what they need so they can find a job or recover in a short period of time. However, using the self-report approach to identify homeless' mental illness is not appropriate. It is also unrealistic to ask someone who is not able to manage his or her life because of mental illness or physical disability to prove himself or herself as homeless with an official paperwork.

The other distinct category is chronical homelessness. Public Law 111-22 also expended the definition of "chronically homeless person" (Authenticated US. Government Information, 2009). Those unaccompanied individuals who have been homeless continuously for one year or on four or more occasions in the last three years, and who had disabilities. In other words, not only families, but also individuals who have been homeless at least 12 months in the past three years with at least seven nights separation each occasion.

The HEARTH Act, became effective on January 4, 2016, added to the definition of chronically homeless those homeless families with an adult head of household or youth where no adult is present who has a disability. The definition of disability specifically includes post-traumatic stress disorder and traumatic brain injury. In addition, a person institutionalized for fewer than 90 days will be considered chronically homeless as long as prior to entering the institution, they otherwise met the definition of chronical homelessness. However, this one-year time restriction on chronical homelessness definition diminishes the effectiveness of the long-term housing approaches and increases the burden to the short-term housing programs. Because the chronical homeless who deserve the PSH assistance cannot apply for it until they have slept on the street for one year, and shelters are most unlikely to welcome them if they either are drug abuse, have mental illness, or have any other unacceptable behaviors. This dilemma results in unsheltered homeless population increases since those homeless people are not qualified for any housing assistance.

In fact, a large body of homeless who live in the city may not be willing to be moved off the place in which they have lived for decades. This information was shared when I interviewed the homeless manager of City of Malibu.[2] He said that homeless people want to be in the city where they know the neighborhood and the people. Homeless' sense of belonging is also mentioned in Winter's research (Winter, 2017). He finds that the street dwellers believe themselves as taxpayers and believe they are entitled for making the decision that is in favor of their interests. Among those street dwellers, those who once accepted social assistance had negative experiences with the services, and frequently gave statements saying they would not use services (Winter, 2017).

To summary who are the homeless and how they are classified, Figure 1-2-1 is used to help understand this target group.

[2] Gittinger, A., personal communication, March 7, 2020

Self reporting / intake worker's observations / certification from a relative decides the person's homeless status.

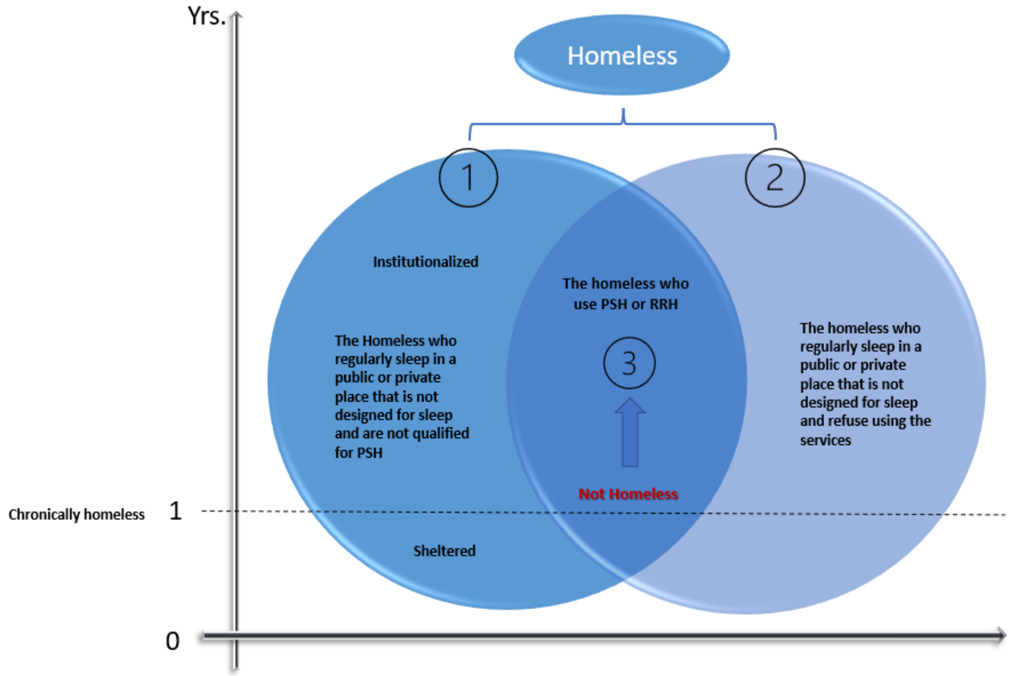


Figure 1-2-1. Who Are the Homeless and How to Identify Them

Figure 1-2-1 depicts various types of homelessness and the City's objective. The goal for the policy maker for solving homelessness is to help all unsheltered homeless people (1 & 2) into homes (3). Simultaneously, to prevent the people who use housing supports from becoming returning homeless.

1.3 Homeless Grants

Section 1.1 introduces which group of people belongs to the homeless who might be eligible for applying for housing and other supportive services. In this section, the available supportive housing services for homelessness mitigation are introduced.

The Homeless Assistance Grants, administered by the Department of Housing and Urban Development (HUD), were first authorized by Congress in 1987 (Perl, 2017). The grants composed of four subprograms during 1992 through 2012. The four components were: the Emergency Shelter Grants (ESG), the Supportive Housing Program (SHP), the Shelter Plus Care (S+C) program, and the Section 8 Moderate Rehabilitation for Single Room Occupancy Dwellings program (SRO). According to Perl (2017), funds for the ESG program were used primarily for the short-term needs of homeless people, while the other three aim to provide longer-term transitional support. The components of the Homeless Assistance Grants were revised when Congress enacted the Homeless Emergency Assistance and Rapid Transition to Housing Act (HEARTH) as part of the Helping Families Save Their Homes Act in the 111th Congress (P.L. 111-22). The HEARTH Act expanded the ESG program in a way which funds can be used for homeless prevention and rapid rehousing. The HEARTH Act also integrated SHP, S+C, and SRO into one program called the Continuum of Care (CoC) program.

Started in FY2011, the ESG program was implemented and the CoC program followed in 2012 (Perl, 2017). Funds for the ESG program can be used for prevention, rapid re-housing, shelters, and supportive services. CoC program funds can be used to provide permanent supportive housing, transitional housing, supportive services, and rapid re-housing. HUD distributes ESG funds to states, counties, and metropolitan areas using the Community Development Block Grant (CDBG) program formula. In contrast, the CoC grants have been distributed through a competitive process which does not rely on the CDBG formula distribution since July 2016. Funding for the Homeless Assistance Grants (HAG) has increased by almost $1 billion in the last decade, approaching nearly $2.4 billion in 2017, over $5 billion in 2019 and 2020, and $2.77 billion in 2021 (HUD, 2021; Perl, 2017). According to HUD (2021), almost 90 percent of total grants are used for the CoC program. The grants are allocated on the following programs and services.

(1) The rapid re-housing, a time-limited permanent housing and stabilization services for homeless individuals and families.

(2) Permanent supportive housing for chronically homeless people with disabled family members.

(3) Transitional housing to help individuals and families (most are the chronically homeless) move to stability within two years.

(4) Support services (provided through housing programs) to help identify and maintain permanent housing.

(5) Planning to improve program monitoring, collaboration, and data collection to drive higher performance at the local level.

According to HUD (2021), before 2018, HUD had prioritized permanent supportive housing, which served people with the highest levels of housing and service needs, especially people experiencing chronic homelessness. More recently, after 2018, HUD has created incentives for communities to use their ESG and CoC resources to expand rapid re-housing.

Funds in the CoC competition are largely used to renew existing grants, but Continuums of Care may also create new projects. According to Perl (2017), in 2017, HUD allowed applicants to apply for new projects at up to 6 percent of Final Pro Rata Need or FPRN. One issue with homeless assistance grants is that HUD has a limited amount of funding to support new projects. The cost to renew existing grants takes up a large share (around 90 percent) of CoC program funds. In 2001, the Senate Appropriations Committee noted that "the CDBG formula has no real nexus to the homeless needs," and urged HUD to hasten its development of a method for counting homeless individuals. In general, factors used to distribute formula funds for programs such as CDBG are based on data collected by government, such as the Census Bureau, that do not consider the funds distributions (Perl 2017). While the best measure of community need for homeless assistance might be the actual homeless population, which is difficult to know. According to Perl, the entities that are in charge of data collection might have their own interests in the distribution of funds.

The Supportive Housing Program (SHP) provided funds for transitional housing for homeless individuals and families for up to 24 months, while permanent housing is for homeless individual with disabilities, and for supportive services. In 2011, nearly 69 percent of total HUD competitive grant funds went to recipients as public housing authorities or SHP grants. Eligible applicants for SHP grants included, states, local government entities, public housing authorities, private nonprofit organizations, and community mental health centers. Grantees could provide either housing together with services or provide services only. At least 10 percent of total SHP funds had to be used for supportive services, at least 25 percent were to be used for projects that served families with children, and at least 25 percent had to be used for projects that serve homeless persons with disabilities (Perl, 2017).

The Single Room Occupancy (SRO) program provided permanent housing to homeless individuals in efficiency units similar to dormitories, with single bedrooms, community bathrooms, and kitchen facilities. In 2011, three new competitive grants were awarded to SRO projects for a total of approximately $3.2 million. The SRO program did not require homeless residents to have a disability and did not fund supportive services. SRO units were funded as part of HUD's Section 8 Moderate Rehabilitation program. The maximum amount that a building owner could spend per unit and still be reimbursed was $23,000 as of 2011 (Perl, 2017). After the

10-year rental contracts expired, they were renewed through the Section 9 project-based rental assistance account on an annual basis rather than through the Homeless Assistance Grants (HAG).

With the rise of unsheltered homelessness, a recent report by the California Policy Lab analyzed the characteristics of the homeless. The researchers find that health and behavioral health and trauma are significant contributing factors to the loss of housing, particularly for unsheltered women (HUD, 2021). HUD also pointed out that people with the longest experiences of homelessness, most significant health conditions, and greatest vulnerabilities are not being served by emergency shelters. This finding indicates that grants may not fully spent by the right people. HUD's Annual Performance Report (APR) data for CoC program indicates that HUD's permanent housing programs admit roughly 30 percent of persons they serve directly from unsheltered situations, while HUD's transitional housing program admits roughly 21 percent of persons directly from unsheltered situations. Some studies report positive outcomes and cost-savings gained from housing and supportive service for the homeless. A 2017 study, for instance, conducted in Orlando showed that placing 58 persons who regularly use jails or emergency rooms into permanent supportive housing resulted in a cost savings of nearly $2.5 million in a single year. Serving people who are the most difficult to serve results in improving their lives and saving money for the public.

The problem is that according to the regulations for the homeless grant distribution, communities are limited to using not more than 10 percent of CoC program funds to serve individuals and families defined as homeless under other federal status unless the community has a rate of homelessness less than one-tenth of one percent of the total population (HUD EXCHANGE, 2009). Such policy creates a problem when the individual homeless population is at large. Los Angeles falls into this circumstance.

To summarize grants and their associated services, Table 1-1 below portraits the Federal grant distribution for confronting homelessness crisis in Los Angeles City and County in 2021.

Table 1-1 Federal Homeless Grants for Los Angeles City and County in FY 2021[3]

Applicant Name	Admin	% Total Grant for Admin	Total Grant for the Applicant	% Total Grant for the Applicant over the Total Grant of the Yr
Housing Authority of the City of Los Angeles	$4,942,935	48.32%	$67,182,003	44.89%
Los Angeles County Development Authority	$2,586,155	25.28%	$36,897,193	24.65%
Los Angeles Homeless Services Authority	$2,189,745	21.41%	$35,953,631	24.02%
City of Santa Monica Housing Authority	$220,382	2.15%	$4,447,586	2.97%
City of Pomona Housing Authority	$114,841	1.12%	$2,141,317	1.43%
Alliance for Housing and Healing dba The Serra Project	$40,283	0.39%	$859,726	0.57%
City of Burbank	$28,700	0.28%	$569,204	0.38%
1736 Family Crisis Center	$34,788	0.34%	$531,763	0.36%
United States Veterans Initiative	$19,319	0.19%	$295,315	0.20%
Upward Bound House	$18,760	0.18%	$286,785	0.19%
A Community of Friends	$12,569	0.12%	$192,130	0.13%
Step Up on Second Street, Inc.	$8,408	0.08%	$144,410	0.10%
The People Concern	$7,120	0.07%	$108,838	0.07%
Su Casa ~ Ending Domestic Violence	$4,860	0.05%	$53,462	0.04%
Total	$10,228,865	100%	$149,663,363	100%

Table 1-1 shows that Housing Authority of the City of Los Angeles (HACLA) received almost a half of the total federal grants in 2021. According to the Grant Inventory Worksheet (GIW) report from HUD, HACLA spent 27,210,046 dollars, 40.5 percent of the total grants, on LA County Department of Mental Health. As of September 30, 2020, the allocated funding from California for homelessness of Los Angeles City and County was 166,113,415 dollars (HCFC Annual Funding Report, 2020)[4]. Even though the homelessness grants from the State for 2021 have not been reported yet, the estimated total annual funds for Los Angeles from

[3] Data source: FY 2021 GIW – HUD
[4] HCFC: California Homeless Coordinating and Financing Council

HUD and California could be around 320 million dollars. Therefore, the estimated total grants for Los Angeles homeless in 2021 would be 470 million dollars. The question becomes whether all the fundings are sufficient for handling 46,000 unsheltered homeless people meanwhile providing sustainable long-term housing and services for existing homeless people. We will discuss it in Chapter 5 in details.

1.4 Key Partners and Stakeholders

Stakeholders are all the agencies which manage homeless fundings and the users of the fundings. On the Federal level, according to Homeless Assistance Grants (HAG) 2022, HUD continues to prioritize key partnerships with local, States, and Federal stakeholders to prevent and combat homelessness. HUD and the Department of Veterans Affairs (VA) are committed to ending veteran homelessness and have implemented joint planning efforts related to data collection and reporting and partnered to develop milestones and strategies to meet the goal of ending homelessness among veterans. HUD, Department of Education, and the department of Health and Human Services (HHS) share the joint goal of ending homelessness among children, families, and youth. Through HUD's Youth Homelessness Demonstration process (YHDP), HUD, HHS, ED, and the United States Interagency Council on Homelessness (USICH) shared data to better understand performance and what interventions and necessary partnerships might be helpful with ending youth homelessness. HUD, HHS, and the Department of Justice (DOJ) jointly found the Federal Domestic Violence and Housing Technical Assistance consortium, aiming to providing training, technical assistance, and resource development at the critical intersection of domestic and sexual violence, homelessness, and housing. According to HAG 2022, HUD is also working with the Department of Labor to help communities better connect people experiencing homelessness to employment opportunities.

To summarize this chapter, homeless definition, homeless grants, and the major key stakeholders are introduced. To have a better understanding about the relationship between stakeholders and roles of combatting the homelessness crisis in Los Angeles, Figure 1-4-1 depicts key stakeholders' functions in combatting homelessness.

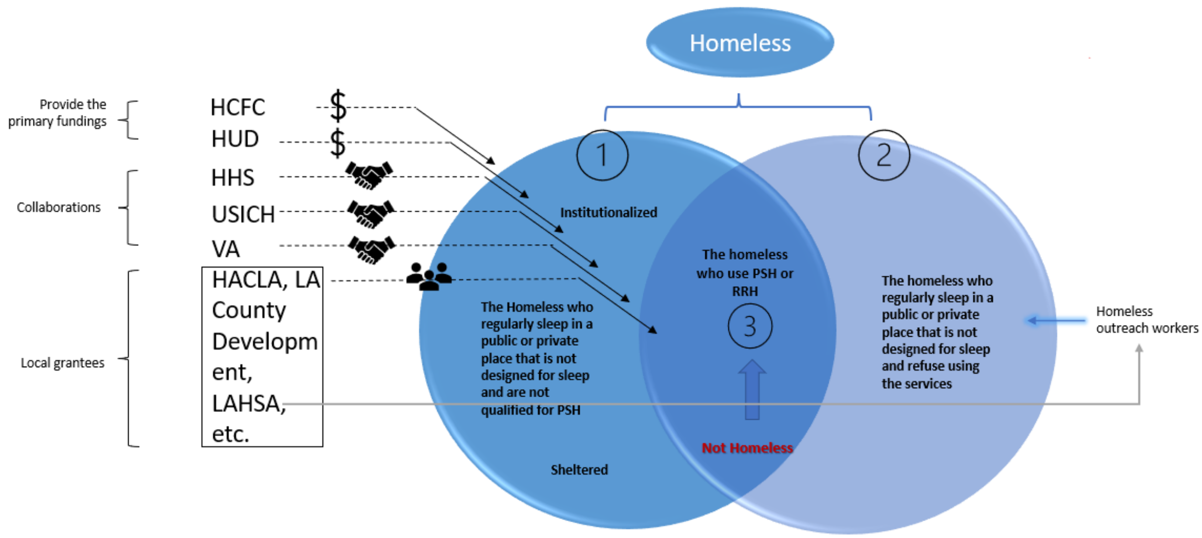


Figure 1-4-1. The Homeless and Key Stakeholders

HCFC (California Homeless Coordinating and Financing Council) and HUD are the two primary sources of homeless fundings. The chart also unveils a difficult circumstance that is when the chronically homeless refuse to use supportive services, the grants and all the efforts of the local government become useless.

Note that in Figure 1-4-1, the overlap section represents the homeless who are using either PSH or RRH and according to the homeless manager of City of Malibu, they are no longer to be the homeless when they are served by these two programs.[5] Even though both RRH and PSH are two components of Housing First Policy, the two programs are different in nature in terms of the length and services of the program. The homeless may need to wait a few years for a PSH housing, but when they move into the PSH program, they are supported by housing and health services. While the homeless may be supported by a RRH program very quickly, but they must exit the program in a few months. In other words, the homeless still must figure out where they can stay after the program is terminated in a few months. If they cannot find a place to stay, then they have to return back on the streets. When they become homeless again, the total number of days for being homeless is from the first day they are back to the street after exiting the RRH but not the first day they became homeless before entering the RRH.

In 2017, a joint transitional housing and rapid rehousing project was implemented. It aimed to serve homeless individuals and families with a focus on obtaining and retaining permanent housing. In 2021, the total federal grants for the joint TH and PH-RRH program was 7,348,166 dollars, 5 percent of total federal fundings, supporting a total 196 units for the homeless. However, if we don't know how to deal with those who are not willing to leave the streets and how to stabilize the homeless who have severe mental illness, it will be unlikely to make a significant improvement on reducing homeless population.

In fact, the housing-based approach for homeless mitigation has been widely adapted by counties but the implementation of the RRH program has not yet yielded the outcome the policy makers expect. Indeed, the homelessness in LA become even worse than 10 years ago. It may make us think there must be something else that worsens Los Angeles homelessness. Recall the homeless system comprises of prevention, homeless housing, and self-efficacy. We have been

[5] Gittinger, A., personal communication, February 7, 2020.

depending on housing to improve the situation, but homelessness is also affected by homelessness prevention and health and social services support.

1.5 Cost and Effective Comparison between RRH and PSH

According to the White House, the federal government was not sure whether the Housing First policy helped reduce the homeless population or not (the White House, 2020). They argued that the relationship between housing support and homelessness could be affected by different data collection methodologies (the White House, 2020). From economical perspectives, knowing the costs of supportive programs and their impact on homelessness is vital . Finding out ways that would yield effective and efficient outcomes on homelessness mitigation is the focus of this study. To evaluate the policy, we need to investigate two aspects, the costs and the outcomes, for the PSH and the RRH programs. In general, the costs for a housed homeless on average is cheaper than an unsheltered or non-housed homeless (LAHSA, 2017b; HUD,2019; Los Angeles County Homeless Initiative, 2019). Studies have found that housed homeless use emergency room services less than street dwellers. More specific, compared to temporary with permanent supportive housing programs, the permanent supportive housing along with consistent social services is better than the temporary supportive housing approach. Given that the permanent supportive housing approach for the chronically homeless tends to be a long-run strategy, there is a need for consistently sufficient funding to support both housing inventory and supportive services. The average annual PSH cost including services and housing per household is around $17,400 or $5,820[6] per person (LAHSA, 2017b). A net cost of the PSH based on 46,000

[6] The average persons per household between 2015 and 2019 in LA County is 2.99 (U.S. Census Bureau, 2019).

chronically homeless in 2020 would be a little bit under 290 million [7] (LAHSA, 2021b). According to HUD 2020, the federal funding for Los Angeles homeless is $140 million for all programs (LAHSA, 2020a). Additionally, there is an equivalent amount of funding from the State particularly for Los Angeles permanent supportive housing (LAHSA, 2020c). With the assumption that the City can properly utilize all the fundings, there is still not sufficient fundings to afford all the supportive programs. If the funding is short, we have to figure out ways on how to reallocate the limited resource. Which program, the PSH or the RRH, should be cut off or expanded? Table 1-5-1 shows the comparison numbers between the cost for the two housing programs and the impact on the homeless. It illustrates that while 0.1 percent of those in RRH return to homelessness, only 0.04 percent of those in PSH return to homelessness at nearly a quarter of the cost (LAHSA, 2017b; HUD, 2019; The Los Angeles County Homeless initiative, 2019).

Table 1-5-1. Housing Program Performance Comparison at Point-in-Time

<table>
<tr><th colspan="4">Cost Comparison between PSH and RRH</th></tr>
<tr><th></th><th>1BR (LAHSA 2017)</th><th>% Homeless return between 2017-2018</th><th>Housing prog. increase rate between 2017 - 2018</th></tr>
<tr><td>Annual PSH Services Cost per Individual</td><td>$1,780</td><td rowspan="2">0.04 (Initiative, 2019)</td><td rowspan="2">0.05</td></tr>
<tr><td>Annual PSH Housing Cost per Individual</td><td>$4,045</td></tr>
<tr><td>Annual RRH per Individual</td><td>$3,612[8]</td><td>0.1 (LAHSA, 2017b)</td><td>1.14</td></tr>
</table>

[7] 46,000 homeless x $5,820/per homeless per year x 1.08, assuming the inflation rate is 8 % inflation rate.
[8] Data source: https://www.countyhealthrankings.org/take-action-to-improve-health/what-works-for-health/strategies/rapid-re-housing-programs#:~:text=Rapid%20re%2Dhousing%20costs%20about,local%20rental%20rates12%2C%2018.

Note that the homeless return from PSH is as low as 0.04 percent while the RRS homeless return is about 2.5 times PSH's. Despite the cost for a one-bedroom unit, the RRH growth rate is almost 23 times PSH.

Suppose that the initial homeless population is 10,000. If the average costs for an unsheltered homeless is $40,000 dollars, then the estimated costs of using the PSH for 10 years would be estimated through below equations.

$$The\ PSH\ Costs = \sum_{i=1}^{i=10} Pop \cdot (1 - 0.04)^{i-1} \cdot (1780 + 4045). \qquad (1.5.1)$$

$$The\ PSH\ Costs = 5825 \cdot \sum_{i=1}^{i=10} 10000 \cdot 0.96^{i-1}. \qquad (1.5.2)$$

$$The\ Costs\ on\ Unsheltered\ Homless = 40000 \cdot \sum_{i=1}^{10} 0.96^{i-1} \cdot 10000 \cdot 0.04. \qquad (1.5.3)$$

In other words, on average, the annual PSH cost for keeping 8,321[9] homeless every year would be 49 million dollars. The cost for returning homeless would be a total of $11 million dollars in 10 years.

The Costs of using the RRH program for the same initial homeless would be estimated by below equation.

$$RRH\ Costs = 3612 \cdot 10000 \sum_{j=1}^{j=10} 0.6^{j-1}. \qquad (1.5.4)$$

$$The\ RRH\ return\ Homeless\ Cost = 3612 \sum_{j=1}^{10} 0.6^{j-1} \cdot 10000 \cdot 0.4. \qquad (1.5.5)$$

The estimated annual cost of using RRH is $9 million dollars for keeping around a total of 1,004 homeless people. The cost for the returning homelessness would be $40 million dollars. Table 1-5-2 shows the costs comparison of the two programs for the same initial 10,000 homeless people in 10 years with different homeless return rate in the RRH program, ceteris paribus.

---

[9] $10000 \cdot \sqrt[10]{1 \cdot 0.96 \cdot 0.96^2 \cdot \ldots 0.96^9} = 8321$

Table 1-5-2 Costs Comparison between the Permanent Supportive Housing and the Rapid Rehousing in 10 Years

Est. \ Prog.	PSH	RRH	PSH/RRH
Base	10000	10000	1.00
Unsheltered homeless population in 10 years	3,352	9,940	0.34
Housed homeless population in 10 years	83,792	14,909	5.62
Total Annual Cost	$ 59,507,428	$48,572,291	1.23

Table 1-5-2 suggests that the average cost for the PSH implementation is 1.23 times RRH's. The effectiveness of the PSH approach on battling homelessness is obvious as it supports over 83 thousand homeless off the streets at the same time only 3 thousand homeless live on the streets.

Compared to the PSH approach, the RRH method is 0.23 time cheaper. It, however, has limited capability on homeless mitigation. Only less than 15 thousand homeless are served, leaving almost 10 thousand homeless still unsheltered.

Chapter 2

Contemporary Research on Homelessness

The following sections in this chapter will examine bodies of work concerning homelessness and the relevant policies that were implemented on combatting homelessness. Section 2.1 begins with the scholars' assertations of the relationship between housing and homelessness and debates over the supportive housing programs. Section 2.2 states homelessness theories and Section 2.3 summarizes the chapter, followed by Section 2.4, addressing present challenges in homelessness research using inductive reasoning approach.

2.1 Literature Review

Economic theory predicts that people will have difficulty paying rent and, in some cases, end up homeless. Clifasefi et al., (2016) described Housing-First as an approach to end homelessness by providing "immediate, permanent, low-barrier, non-abstinence-based supportive housing for individuals with the lived experience of homelessness. They argue that the Housing First policy attempts to improve many domains for the homeless in two primary ways: providing the affordable housing and the access to assertive services (Clifasefi et al., 2016).

However, despite the number of chronically homeless people living on the nation's streets and shelters dropping to as low as 30 percent between 2005 and 2007, the Housing First approach was faced with many critiques (Stahnhope et al., 2011; Kowarsch & Yang, 2021). Research has suggested that an emphasis on housing services could negatively impact communities' efforts to end homelessness and that communities should focus instead on homelessness prevention and moving homeless people into permanent housing (Fowler et al., 2018). Homelessness prevention offers another viewpoint by decreasing in-flows for services while benefiting households by avoiding the social, emotional, and financial costs of homelessness (Fowler et al., 2018). The Housing First approach prevents people from seeing the difference between reacting to homelessness and proactively managing homelessness.

A thorough review of literature revealed that the rate of homeless consumers entering the system contributed to the size of the homeless population. As a result, there are advantages of using the Housing First approach in combination with a homeless prevention program to address the homeless crisis. Although most findings support the Housing First approach, future research on an integrated approach that combines homeless prevention as well as supportive housing and services could help yield better policies for Los Angeles homelessness. A study conducted in Italy suggests that the homeless' mental health is improved when they are treated as normal people and taken care of by professional health providers (Basaglia, 1975; Prtacolone et al., 2015).

2.2 Theory

Theorized studies on homeless were popular in the 90s in UK (Anderson et al., 1993; Drake et al., 1981; Evans, 1991; Evans &Duncan, 1988). Some complex typologies of homelessness exist in this literature (e.g., Huston & Liddiard,1994). According to Drake et al., 1981; Evans, 1991; Watson & Cooper. 1992, the degree of diversity in backgrounds, housing histories, support needs, and housing preferences of homeless people affect homelessness. But most findings were revealed through policy orientated survey research, which were designed and managed by government. As Neale's argument, "the under-theorizing of homelessness is most apparent in those reports which have been commissioned by government departments." (Neale, 1997). Neale argues that the findings derived from the above approaches most likely are empirical-based correlations rather than causality.

Historically, Johnson et al. (1991) argued that there are two contradicting debates about the causes of homelessness. One is structural explanation, the second is the individual or agent explanation. The structure factor theory emphasizes the impact from the macro level in the social-economic system. Higher poverty rate, unemployment rate, and housing prices all belong to a structure explanatory perspective. The believers of structure theory support the implementation of housing policy as the primary approach to reduce the homeless population, Meanwhile, agency explanations consist of two threads. The first thread asserts that individuals are responsible for their homelessness (Neale, 1997). The second thread poses a proposition that the personal characteristics and hardship result in homelessness. The supporters of the second thread argue that health and supportive assistance will be helpful in keeping the homeless people function.

The structural and individual theory models provide a foundation that helps explain homelessness. But why the homeless people choose to live in the City of Los Angeles? Peterson and Rom (1990) argued that the poor people will rationally choose to relocate to the place which offers more services that meet their needs. They also argue that states prevent homeless migration by lowering benefits relative to neighboring states (Peterson and Rom, 1990). Winter argues that social connections attract the homeless to the cities (Winter, 2017). From Peterson and Rom's perspective, they assume that the homeless migrants are rational and know the place that provides the benefits they need. By contrast, Winter focuses on the long-term street dwellers who have been part of community and lived there for decades.

2.3 A Summary of Scholars' Key Findings

Some academic literature confirm that higher home prices are indeed associated with higher rates of homelessness (the White House, 2019). Corinth (2017) used panel data on Continuum of Care programs (CoCs) and found that a one percent increase in median rent within a CoC is associated with a one percent increase in its rate of homelessness. Quigley et al. (2001) found similar results using variation over time within counties in California, with a one percent increase in median rent associated with a 0.9 to 1.2 percent increase in the rate of homelessness for certain conditions. These findings support the structural theory that providing housing is the direct approach to confront homelessness.

Many reasons cause the vulnerable group people to be homeless. Even the seemly contradicting theories and their associated findings, from certain aspects, provide various pictures to portray homelessness in different ways. However, to be able to effectively solve Los Angeles homelessness, despite the reasons mentioned above, we shall also evaluate homelessness from a system dynamics perspective.

2.4 Challenges

In previous sections, the evidence suggests that the housing price, rental price, and individual factors contribute to homelessness increase. When people no longer pay their rent to the landlord, they are evicted by local law enforcement and begin the homeless journey. Since more and more homeless people use public goods that are contributed by all taxpayers in the city, if Los Angles had sufficient fundings to house all of them, it would not be a problem. It is a problem when the local government lacks financial and human resources to meet homeless people's needs and move all of them off the streets.

Los Angeles implements a scoring system, Coordinated Entry System, to prioritize the homeless due to the limited resources and challenges. The LA City and County coordinated entry system (CES) is intended to support participant choice in the matching process but can also impede those experiencing chronic homelessness from receiving the services they need. The high acuity score[10] families are prioritized first and are matched to PSH. The youths from high acuity score families are prioritized second and matched to either a permanent supportive housing or rapid re-housing program. Other individuals who score high are prioritized third and matched into a rapid rehousing program (LAHSA, 2017a, 2018). Anyone who scores below the threshold does not qualify for a PSH or rapid re-housing (LAHSA, 2017a, 2018). During the pandemic, LAHSA has prioritized people (age 65 and above) with high acuity score needs and who face high risks of death or severe illness from exposure to COVID-19 (LAHSA, 2021c). Appropriately, the Coordinated Entry System (CES) tends to prioritize families with youths, followed by single youth and single adults experiencing homeless. Unsurprisingly, most unsheltered chronically homeless individual adults are left without support as their scores are not high enough for the housing programs that they want. Figure 3-1 below portrays dynamic changes among enrollment (purple), bed capacity (yellow), and beds used (red); this demonstrates that housing programs' bed inventory is going unfilled.

[10] Acuity score is an indicator of the severity of a homeless person and the level of attention or service she will need from professional staff (Taber's Medical Dictionary, 2021).

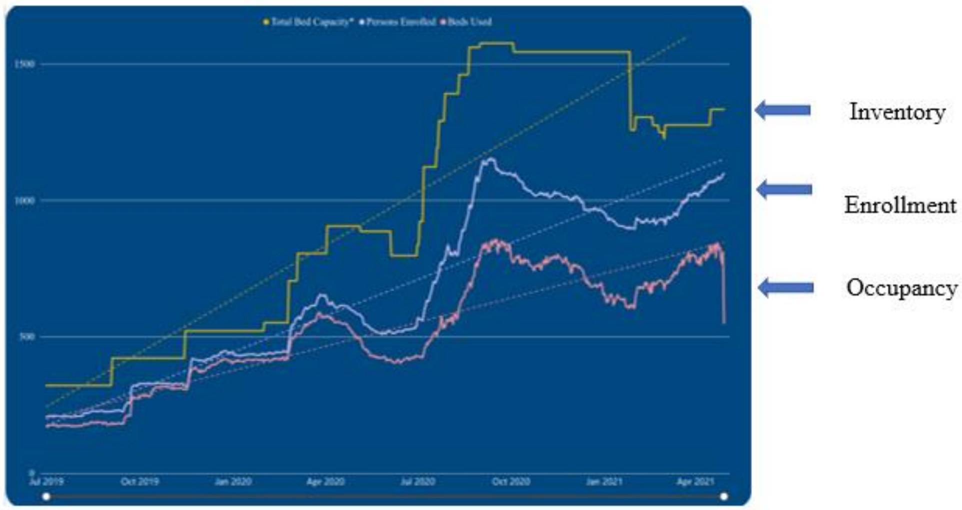


Figure 3-1. Los Angeles Homeless Enrollment and Occupancy between 2019 and 2021 (LAHSA, 2021a)

Note that with a higher bed inventory level (the yellow line), the enrollment level (the purple line) is below the housing's capacity, and the bed occupancy (the red line) is below the enrollment. Apparently, bed inventory is not fully utilized. The reason for unused beds is not clear, but it is assumed that either the homeless people don't want to accept the housing assistance, or they can't use it because of the score system block them from using it.

Los Angeles City and County used descriptive analysis and prediction models as guidance for strategical and tactical planning. The irony is that the statistical models fail to effectively reveal the mechanism of homelessness and might be unable to discover the cause of the homelessness increase which is produced by the interactivities among existing homeless people, community, government supportive teams, police, and policies that deteriorate social injustices. The following example is used to demonstrate how a mis-specified regression model generate misleading conclusion. Suppose a linear regression only has two independent variables: unemployment rate, and housing price, and an independent variable is homeless population. The regression allows us to test the relationship between poverty rate and homelessness, holding the housing price constant, or vice versa. The challenge is that a model's misspecification leads to dependency between one or more regressors and the error term. This situation violates the Gauss-Markov theorem for the ordinance least squares technique (OLS) to produce the best linear unbiased estimates (Gujarati et al 2019). In our case, the linear model has two theorical regressors, the unemployment rates and housing prices. Some personal characteristic regressors such as a person's mental health condition, physical disability, and social ties, however, are excluded. The exclusion of the theoretically important variables results in model misspecification. Furthermore, we confidently believe that mental health affects people's employment. Without including a mental health variable in the linear model, the disturbance term, which captures the effect of mental health on the unemployment rate and the unemployment rate become dependent. The independent variable of unemployment can't be held constant anymore. Therefore, when individual factors are excluded, the regression most likely faces a misspecification issue.

The next challenge to using statistics is that the regression modeling approach is data dependent. The quality of the work is determined by the quality of the data. Homeless data collection starts in 2007. By law, participants (usually counties and cities) are only required to submit homeless data every two fiscal years. From 2007 to 2022, there are about eight reports from Continuum of Care participants stored in HUD's submission system. Regardless of discrepancy in the data collection methodology, eight observations are unlikely to reveal a true relationship in a regression model.

There is another problem using survey data collection. It is that how to collect the variables of interest and how valid can the research be using a questionnaire approach for data collection. Can we personally ask an apparently mental ill homeless person about his or her mental severity level from a scale of 1 to 5 (e.g., a Likert method)? Unless we are health providers or police. It is difficult to know such detailed and personal information accurately. Even if such information is recorded, it is questionable if it is based on the answer provided by a person who is unable to answer. What score a social worker can grade on the person's mental health: If the homeless outreach worker doesn't think the homeless has a mental health issue or slight issue based on the normality during the conversation. This homeless may be ruled out as mentally ill homeless. Such a survey is manpower based and becomes subjective and poorly represents the true status of the general homelessness.

Even though there are conditions and assumptions which need to be fulfilled when using statistical analysis, an ordinary least squares regression approach can be efficient if all the pitfalls mentioned above are eradicated.

Chapter 3

Research Design and System Dynamics Model

3.1 Research Design

My objective in this dissertation is to identify the policy most likely to respond effectively to the Los Angeles homeless crisis in a short period. My approach differs from the approaches of other relevant studies in three ways: (1) As regards method, this study applies a combined method that comprises both deductive (an SD simulation model) and inductive (a regression model) approaches. (2) It focuses on uncovering efficient solutions for both chronically homeless and non-chronically homeless people. (3) Rather than seeking necessarily to improve existing policies by tinkering with them, I seek instead to elaborate the policies most likely to ease the challenge of homelessness in Los Angeles in a limited period.

Prevention and long-term supportive housing are the common approach to ease homelessness. In Los Angeles. according to LAHSA, from 2018 to 2019 LAHSA prevented 1,472 adults from becoming homeless, with of 1,298 of them remaining housed at the end of the year. In Europe, Busch-Geertsems (2014) find that the permanent supportive housing has been considered a highly successful way of ending homelessness for homeless people with severe support needs and helping them to sustain a permanent tenancy in Amsterdam, Copenhagen, Glasgow, Lisbon, and Budapest.

Fowler et al. (2017; 2018) and Nourazari (2021) evaluated the impact of homelessness prevention, rapid re-housing, and PSH on homelessness using SD modeling. The Housing First approach, currently embraced in Los Angeles, comprises homelessness prevention, rapid re-housing, and PSH programs. Focusing on the key aspects of this approach, the SD model I have used in this study features three subsystems: (1) a homelessness prevention subsystem, (2) a short-term housing programs subsystem, and (3) a PSH program subsystem. This model not only incorporates widely used strategies but also makes possible the assessment of specific policy levers and parameters setups that might be expected to vary in light of Los Angeles policy makers' interests. In theory, then, this model can be applied anywhere else:

1. If the same policy levers are used, then the model only needs to be updated to reflect the initial values for the parameters.
2. If the same policy levers are not employed, indicators need to be added or removed as appropriate and the initial values for the relevant parameters need to be set in light of the conditions being reviewed.

I have conducted an OLS regression as the inferential analysis I have used to identify key homelessness prevention factors. I have conducted initialization, validation, scenario analysis, global sensitivity, and equilibrium analyses to evaluate the SD model's robustness. Table 3-1 outlines the key research methods, the key research techniques, and their purposes.

Table 3-1 Research Design

SD Model	**(1) Prevention:**	*the OLS Regression is used aiming to support the argument that eviction is the key driver for new homeless increases*
	(2) Short-term Housing: Shelter, Transitional housing, and Rapid re-housing	
	(3) Long-term Housing: Permanent Supportive Housing	
Testing Stage	**1. Structure Validation**: Homeless manager of Malibu **2. Initialization**: Based on published reports and simulated estimates **3. Model behavior validation**: Unit check & Comparison between simulated data and empirical data	
Production Stage	**4. Scenario analysis:** Evaluate the impact of a policy on homelessness **5. Sensitivity analysis**: The global impact of the multivariate simulation. The variables are identified through scenario analysis. **6. Equilibrium** analysis: Seek the optimal strategy and the conditions required for a minimal homeless population	
Recommendations	The ideal policy and its expected outcome; the second best and its expected outcome; the bottom line and its outcome	

3.2 Ordinance Least Squares Regression

In the prior section, some pitfalls of using an Ordinance Least Squares regression were addressed. However, an OLS regression can be efficient, and the regression result is intuitive when Gaussian-Markov's assumptions are fulfilled. The California Affordable Housing Association in its 2019 annual report claimed that Los Angeles should provide more affordable housing to ease homelessness. Recall the structural theory suggests that high housing prices lead to an increase in homeless population. Therefore, the independent variables are rental stability and housing affordability. In addition, the index of displacement pressure as the indicator for eviction is also considered an important indicator for homelessness.

The sample data was retrieved from the public open database provided by Los Angeles Mayor Eric Garcetti's Office in 2019.[11] The dataset covers from 2015 to 2017. Since the time span is short, the dataset is converted into a cross-sectional data frame by aggregating the variables so that each observation gets an average value point for every numerical variable. It is assumed that using aggregate data projects a long-term relationship between variables.

The dependent variable is the unsheltered homeless population. The theoretical variables are the index of displacement pressure (IDP), the Rent Stabilization Ordinance (RSO), and the affordable housing score. IDP is applied at the census tract level for tracts where equal to or greater than 40 percent of households earn less than the City's median income. According to the Mayor' Office, this variable aims to measure areas with a high concentration of existing residents who may have difficulty absorbing massive rent increases that often accompany revitalization. In other words, the IDP score captures the intersection between housing price gains and the resident's hardship with living in the area. A higher IDP increases the likelihood of being displaced in the area.

RSO is administered by Los Angeles to protect tenants from excessive rent increases while allowing apartment owners a reasonable return on their investment.[12] In the dataset, RSO per occupied housing unit is a ratio of RSO units over occupied housing units. Affordable housing score, on the other hand, is an index that aims to measure the level of housing affordability in the area. A higher RSO score indicates that the more housing in the area is price-controlled. The affordable housing score aims to measure the housing affordability in an area. The higher the score is the more affordable the housing price will be.

[11] https://geohub.lacity.org/datasets/lahub::los-angeles-index-of-displacement-pressure/about

[12] https://geohub.lacity.org/datasets/lahub::rent-stabilization-ordinance-service-areas/about

The control variables include zip code which is used to control the spatial characteristics, the median household income, and the percentage of population who don't have health insurance. The control variables are used for reducing the bias that is caused by model misspecification. Table 3-2 is the data descriptive summary about the sample dataset.

Table 3-2. Descriptive Summary Table of Sample Dataset.

Variable Name	count	mean	std	min	0.25	0.5	0.75	max
Unsheltered Pop (people)	665	24.78	55.73	0.00	7	14	27	1110.00
IDP (index)	665	26.36	11.44	2.04	17.41	23.83	34.27	70.47
RSO Units (units/occupied housing unit)	665	54.27	23.62	0.18	37.83	56.59	71.7	116.10
Affordable Housing Score (index)	665	6.10	13.88	0.00	0	0	0	94.37
Median Household Income (US dollars)	665	41941.11	13107.96	10388.33	32181.5	39703.33	50706.5	85924.00
Half Income for Rent (%)	665	35.65	8.87	9.00	29.29	35	41.33	64.77
No Health Insurance Pop (%)	665	22.24	8.05	3.55	16.85	21.7	27.03	55.20

Note that the homeless population is highly right skewed as the most unsheltered homeless are clustered in a few census tracks. The histogram and box whisker plot in Figure 3-2-1 portrays the unsheltered homeless population in the sample set.

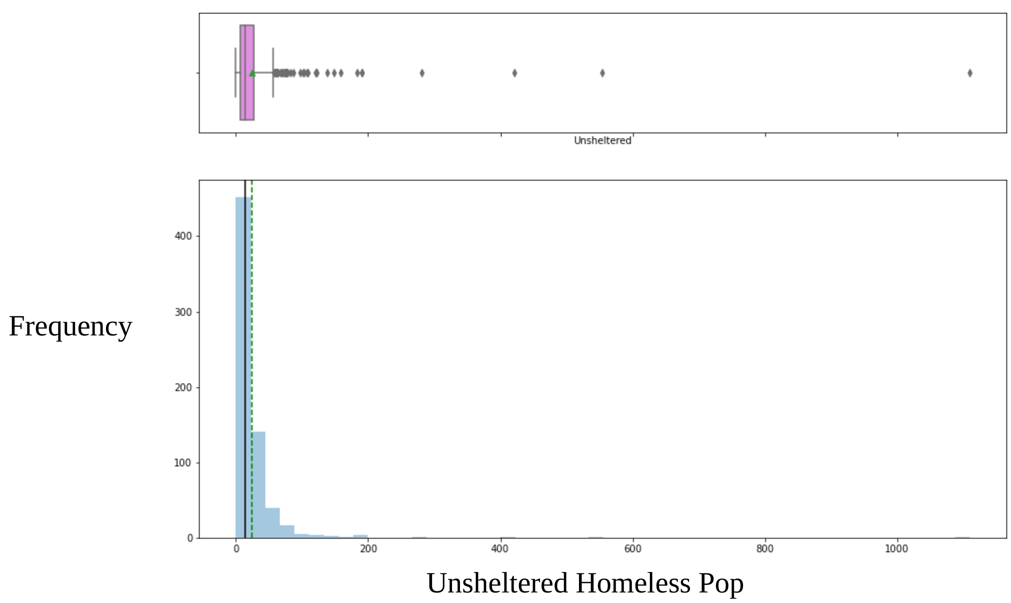


Figure 3-2-1. Box Whisker Plot and Histogram for Unsheltered Homeless Population

The x-axis is the unsheltered homeless population in both plots, and the y-axis in the histogram plot is the frequency corresponding to the homeless population.

Due to the non-normal distribution in the unsheltered homeless population, t-statistics may violate the Gauss-Markov assumptions for OLS regression to produce the best linear unbiased estimator. But based on the Central Limit Theorem, the sample means of each reasonably sized sample that is randomly drawn from the population using Monte Carlo and boost trapping techniques are normally distributed.

$$Y = a_i + \sum_{i=1}^{665} \sum_{j=1}^{8} \beta_j x_{ij} \cdot \overline{e_j} + \varepsilon_i. \quad (1)$$

Where a_i is the linear model's y-intercept.

- Y is a linear function of x and $x \in \mathbb{R}^n$.
- $\overline{e_j}$ are the vectors in $\mathbb{R}^n$with 1 in the ith position and 0 elsewhere.
- β_j $are\ the\ estimated\ coefficients.$
- x_{ij} $are\ the\ value\ point\ of\ independent\ viarables\ at\ row\ i\ and\ column\ j.$
- $x_{ij}\overline{e_j}$ $are\ vectors\ of\ the\ independent\ variable\ at\ row\ i\ and\ column\ j.$
- ε_i $are\ the\ value\ of\ the\ white\ noise\ for\ the\ ith\ variable.$

For convenience purpose, the regression model is denotated in below matrixes form.

$$\begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \\ \vdots \\ Y_{665} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \vdots \\ \alpha_{665} \end{pmatrix} + \begin{pmatrix} x_{1,1} \ \dots \ x_{1,8} \\ x_{2,1} \ \dots \ x_{2,8} \\ x_{3,1} \ \dots \ x_{3,8} \\ \vdots \\ . \\ . \\ x_{665,1} \ \dots \ x_{665,8} \end{pmatrix} \cdot \begin{pmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ \vdots \\ e_{665} \end{pmatrix} \cdot \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \vdots \\ \beta_8 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \vdots \\ \varepsilon_{665} \end{pmatrix}$$

where the sample size (non-missing value observations) is 665. There are 8 independent variables including the intercept.

For the OLS approach, the coefficients are estimated based on the least total distance squared between the values of the dependent variable in the dataset and the estimated value of the dependent variable.

When the first order derivative $\frac{\partial(\sum_1^{665} e_i^2)}{\partial \beta_i} = 0.$ (2)

Use equation (3) to solve equation (2)

$$\sum_1^{665} \varepsilon_i^2 = \varepsilon \cdot \varepsilon' = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon 4 \\ \vdots \\ \varepsilon_{665} \end{pmatrix} \cdot (\varepsilon_1 \ \ \varepsilon_2 \cdots \varepsilon_{665}). \tag{3}$$

Then the estimated coefficients using OLS approach can be calculated by equation (4).

$$\hat{\beta} = (X'X)^{-1}X'Y = \left(\sum_{i=1}^{665} x_i{}'x_i\right)^{-1} \cdot \sum_{i=1}^{665} x_i y_i. \tag{4}$$

Where $(X'X)$ is invertible.

$X' represents\ the\ transpose\ matrix\ of\ the\ independent\ variables.$

$X\ represents\ the\ matrix\ of\ the\ independent\ variables.$

$Y\ represents\ the\ matrix\ of\ the\ dependent\ variables.$

$(X'X)^{-1}\ represents\ the\ inversed\ matrix\ of\ the\ produce\ X'X.$

$x_i'\ stands\ for\ the\ value\ point\ for\ the\ ith\ independent\ variable\ in\ a\ transpose\ matrix.$

$x_i\ stands\ for\ the\ value\ point\ for\ the\ ith\ independent\ variable.$

$y_i\ stands\ for\ the\ value\ point\ for\ the\ dependent\ variable\ that\ responds$

$the\ ith\ independent\ variable.$

One test must be taken when dealing with cross-sectional data is heteroscedasticity test. A plot of residuals of the OLS regression against independent variables of interest are displayed in Figure 3-2-2.

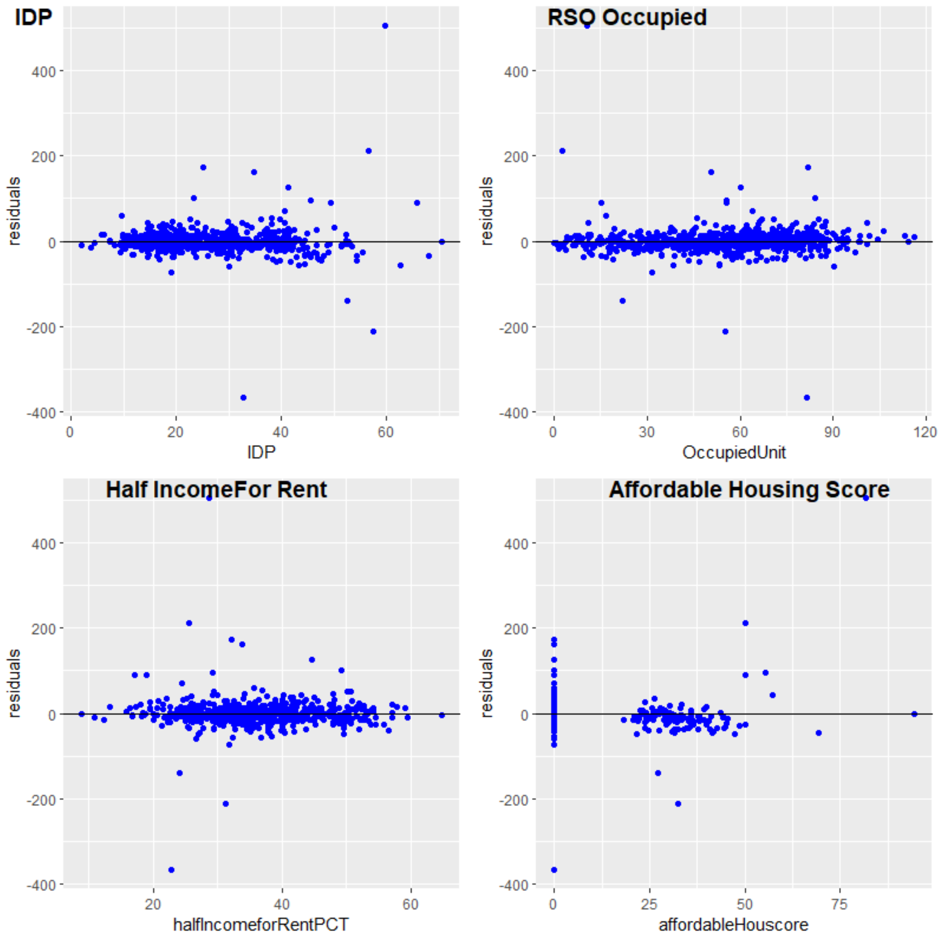


Figure 3-2-2. Residuals against Independent Variables. The plots indicate that most data points in the sample are scattered around zero excepting some extreme values which most likely are associated with the values of the independent variable.

The Breusch-Pagan test and the White test are conducted to confirm heteroscedasticity. The main idea of the Breusch-Pagan test is to find out whether the coefficients for all independent variables' variances in the model are the same and equal zero.

$$\sigma_i^2 = f(a_0 + a^T X_i). \qquad \ldots\ldots\ldots\ldots \qquad (5)$$

Where $a^T = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_p \end{pmatrix}$ is a p-vector of coefficients and independent to the coefficients β.

X_i Can be some of all independent variables.

The null hypothesis is that the model has homoscedasticity, meaning $a_p = 0\ for\ all$. The alternative is that the model is heteroscedasticity, or one of $a_p \neq 0$.

$$H_0: a_1 = a_2 = \cdots = a_6 = 0$$

$$H_a: a_i \neq a_{j,} \quad where\ \forall\ i \neq j \text{ and } i, j \in [1, p]$$

The detailed procedure for the Breusch-Pagan Test are as follows:

a. Let's define the estimated residual variances from equation (1):

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{665-89} \sum_{i=1}^{665} e_i^2. \tag{6}$$

$$g = \frac{e_i^2}{\hat{\sigma}_\varepsilon^2}. \tag{7}$$

Where $g\ is\ the\ proportion\ of\ the\ residiual\ variance\ that\ is\ explained.$ $by\ the\ ith\ data\ point\ in\ the\ dataset\ with\ losing\ one\ degree\ of\ freedom.$

Next, let's fit a linear regression with the original data X as the predictors and $g = [g_1\ g_2 \ldots\ g_i]'as\ the\ response$:

$$g = a_0 + a^T X + u. \tag{8}$$

$$\hat{g} = X\,\hat{a}. \tag{9}$$

$$\sum_{i=1}^{665} g\hat{g} = g'\hat{g}. \tag{10}$$

$$LM = \frac{1}{2}\sum_{i=1}^{665} g\hat{g} = \frac{1}{2}[g'X(X'X)^{-1}X'g]. \tag{11}$$

where $\hat{a} = (X'X)^{-1}X'g$, LM is Lagrange multiplier test and denoted by "BP" in R.

Lastly, we can use Chi-statistics to evaluate the null hypothesis

$$H_0 = LM \sim \chi_{p-1}^2. \tag{12}$$ [13]

Alternatively, we can calculate the F- statistics to evaluate the null hypothesis.

[13] https://gregorygundersen.com/blog/2022/01/31/breusch-pagan/

The Breusch-Pagan test is conducted in R software, the result of BP score using equation (11) is 20305, the p-value for the null to be true approaches zero. It suggests at the critical level of 0.05, we reject the null hypothesis and conclude that there is statistically significant evidence suggesting the existence of heteroscedasticity.

The Breusch-Pagan test depends on the assumption of normality (Gujarati et al, 2012). A more relax test, the White's general heteroscedasticity test is also performed. To do so, the model's residual $\hat{u}_i$ first are estimated based on equation (1), then use following regression formula to evaluate the alphas:

$$\hat{u}_i{}^2 = a_0 + a_1 X_1 + a_2 X_2 + \cdots + a_m X_1{}^2 + a_{m+1} X_2{}^2 + a_{m+2} X_1 X_2 + \cdots + v_i. \quad (13)$$

Alternative equation can be as follows:

$$\hat{u}^2 = \delta_0 + \delta_1 \hat{y} + \delta_2 \hat{y}^2 + v. \quad (14)$$

We can use LM test to evaluate the null hypothesis:

$$H_0: \delta_1 = \delta_2 = 0.$$

The White statistics score computed in R is 526, the p-value at critical value of 0.05 is close to zero, meaning the null hypothesis of $\delta_1 = \delta_2 = 0$ is unlikely true. The White test also suggests the existence of heteroscedasticity of the OLS model.

Based on the BP and the White test results, there are evidence suggesting that the data has heteroscedasticity. To diminish the impact of heteroscedasticity on the estimates, the robust standard error method is applied.

To get robust standard errors, we need to transform the variance-covariance matrix (VC) so that the covariances laying on the diagonal of the VC matrix are constant. The Huber-White robust standard errors can be calculated through equation (15).

$$var(\beta) = (X'X)^{-1} X' \sum(u^2) X (X'X)^{-1}. \quad (15)$$

Where u^2 are the squared residuals of the OLS model or equation (1).

The heteroscedasticity is solved by using the robust standard. The second important test is to examine multicollinearity. The model also passes the multicollinearity test based on the small values of variance inflation factor (VIF). Multicollinearity emerges when three or more variables, which are highly correlated, are included within a model. The VIF quantifies the severity of multicollinearity in an ordinary least squares regression analysis. To find the VIF score for each independent variable, a set of equations are used to find all R squared for every independent variable of X:

$$X_{1i} = a_0 + a_2X_2 + \cdots + a_6X_6 + e \rightarrow {R_1}^2 = 1 - \frac{\sum_{i=1}^{n}(X_{1i} - \widehat{X_{1i}})^2}{\sum_{i=1}^{n}(X_{1i} - \overline{X_{1i}})^2}$$

$$X_{2i} = a_0 + a_1X_1 + \cdots + a_6X_6 + u \rightarrow {R_2}^2 = 1 - \frac{\sum_{i=1}^{n}(X_{2i} - \widehat{X_{2i}})^2}{\sum_{i=1}^{n}(X_{2i} - \overline{X_{2i}})^2}$$

$$\vdots$$

$$X_{6i} = a_0 + a_1X_1 + \cdots + a_5X_5 + z \rightarrow {R_6}^2 = 1 - \frac{\sum_{i=1}^{n}(X_{6i} - \widehat{X_{6i}})^2}{\sum_{i=1}^{n}(X_{6i} - \overline{X_{6i}})^2}$$

Then, the $VIF_i = \frac{1}{1-{R_i}^2}$.

The VIF scores are computed in R and the results are shown in Figure 3-2-2.

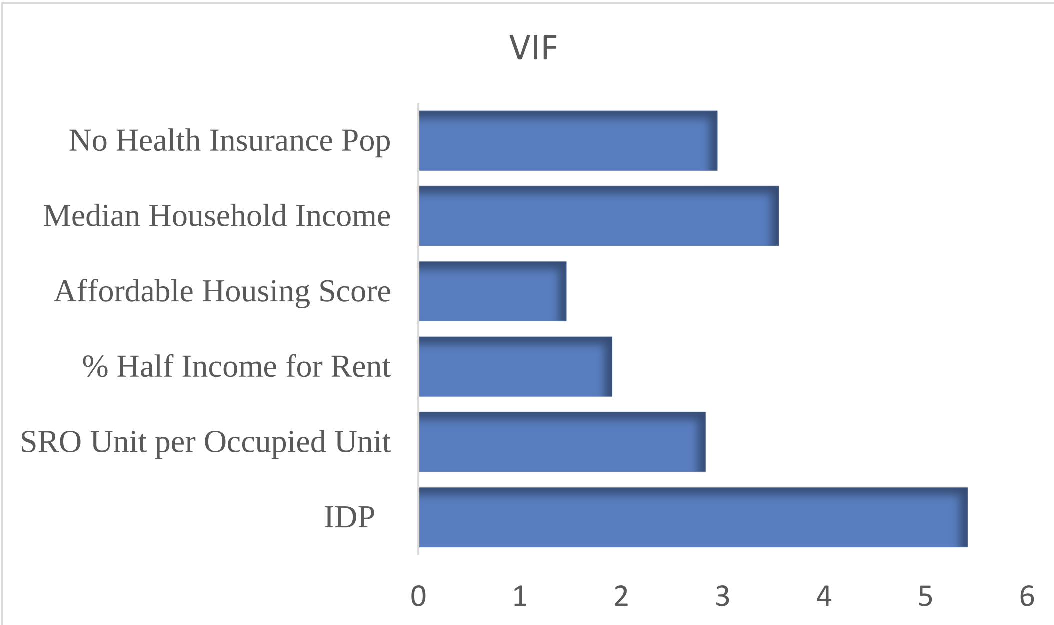


Figure 3-2-2. Bar Chart on VIF Scores

The VIF result indicates there is not major multicollinearity in the OLS model as the scores of each independent variable is less than 10.

Finally, after examining heteroscedasticity and multicollinearity and using robust standard errors, the OLS model's result is displayed in Table 3-2. All estimated coefficients in the table are standardized.

Table 3-3. OLS Regression Result for Homeless Prevention

Unsheltered Homeless Population		
Heteroscedasticity consistent Standard Error		
	Standardized Coef.	P-value
IDP	**0.21**	0.006**
	(-0.38)	
RSO Occupied Unit	**-0.26**	0.004 **
	(0.21)	
HH Pay Half Income for Rental (%)	**-0.07**	0.003 **
	(0.15)	
Affordability Score	-0.08	0.21
	(0.25)	
Median HH Income	**-0.19**	0.01 *
	(0.0003)	
No Health Insurance	-0.01	0.8
	(0.28)	
Significance: critical level of 0.05		
N: 655	Adj. R-squared: 0.54	
RMSE	34.91	

The result suggests that a higher displaced pressure has a positive and statistically significant impact on unsheltered homeless. A community which has lower score in the rental stabilization ordinary index has more unsheltered homeless. A higher median household income has a positive impact on unsheltered homeless mitigation. Compared to other scholars' assertations, the regression result in this study suggests that the household paying half or more income for rent has a negative impact on unsheltered homeless. The housing affordability is insignificantly associated with unsheltered homeless. The evidence indicates the California affordable housing program might not be relevant to homeless prevention. Indeed, the regression results suggest that the homeless prevention strategy should focus on the eviction prevention, including but not limited to the direct replacement for the discharged homeless.

The statistical analysis unveils some important properties of the relationship between the median rent, eviction, affordable housing, and homelessness. Since the regression model does not include homeless housing programs, it is not clear that how the current housing approaches effect Los Angeles homelessness. Kowarsch and Yang (2021a) conducted an agent-based modeling approach to simulate the impact of RRH and PSH and social services on LA homelessness. They assert that social workers have the most impact on decreasing unsheltered homeless population as well as on increasing the number of the homeless in receiving mental treatment. Kowarsch and Yang conclude that the community-based special cares play a vital role in improving the mental condition of unsheltered homeless so that more homeless can successfully be stabilized through housing programs. In addition, they find that, compared to the transitional housing program, the RRH does not have a superior impact on reducing unsheltered homeless population. Also, based on Kowarsch and Yang's one study on the evaluation of homeless prevention, they proposition that compared to homelessness supportive housing approach, the homelessness prevention has a greater impact on homelessness mitigation.

3.3 System Dynamics Modeling

Forrester wrote, "human beings are capable of using the methods of simulation to determine the behavior of complex systems" (Forrester, 1958). Also, it has been found that people are as adaptable to the more abstract strategic planning as they are to tactical decision making once their outlook has been lifted to the broader and longer-range picture (Forrester, 1958). In Sterman's Business Dynamics, he wrote, *"System dynamics is a perspective and set of conceptual tools that enable us to understand the structure and dynamics of complex systems. System dynamics is also a rigorous modeling method that enables us to build formal computer simulations of complex systems and use them to design more effective policies. Together, these tools allow us to create management flight simulators-micro worlds where space and time can be compressed and slowed so we can experience the long-term side effects of decisions, speed learning, develop our understanding of complex systems and design structures and strategy for greater success."*

Fowler et al. (2019) conducted a system dynamics simulation approach to examine the impact of homeless prevention. They concluded that from the perspective of the complex adaptive system, the prevention program provides a leverage point within the system; small efficiencies in keeping people housed yield disproportionately large reductions in homelessness. Nourazari et al. (2021) used system dynamics simulation approach to investigate current homeless policy. They argued that the increases in affordable permanent housing units, the utilization of transitional housing units or shelters, and accessible preventative services to at-risk populations before the onset of homelessness lead to decrease in homeless population.

System dynamics simulation is a tool which allows us to set the conditions in order to simulate the outcomes under various policies in the system. Using feedback loops along with system delays between stages or levels, the model depicts the causal relationship between a set of policies and homelessness. System delays causes outcome fluctuation. The longer a delay is, the more unpredictable it will be. Delay is an important feature in system dynamics. For example, the homeless manager may not know the total unsheltered homeless head counts until the volunteers count them once every two years. How a policy can respond to homelessness if the policymakers don’t know how bad or well the situation is. Another example is the waiting time for the homeless to be served by PSH programs. Is shorter waiting time better than longer? Yes if you are homeless people; No if you are taxpayers. The shorter waiting time may exhaust limited resources quickly. The system dynamics model can answer the questions which the policy makers are uncertain about but may be important to solve homelessness.

Lastly, SD model is not heavily data dependent. But system dynamics simulations are produced by rigorous mathematical equations. The simulated results allow us to test the homeless prevention policy and housing policy under some assumptions. This helps LA policy makers find out more insights without the access to a homeless database. Moreover, the relationship between causes and homelessness is more complicated and involves higher order derivatives. With the supplement support on homeless prevention evaluation using regression modeling approach, the system dynamics simulation modeling and the regression modeling together provide strong evidence for policy makers to consider.

3.4 The System Dynamics Model Architecture

In the prior section, using OLS regression, the key factors for homeless prevention have been identified. A standardized deviation increase in eviction is associated with a 0.21 standardized deviation increase in the unsheltered homeless population; A standardized deviation increase in the occupation in rental controlled housing is associated with a 0.26 standardized deviation decrease in the unsheltered homeless population. In this section, eviction is used in the homeless prevention system in the system dynamics model. For those housing indicators that are excluded in the OLS are also included in the housing subsystems in the SD model.

Based on the investigation mentioned in the prior chapter, key prevention policy levers are identified. The next step is to find out the important policy levers for housing. In order to do so, there are a few questions that must be addressed. First, are the majority homeless people who need long-term continue housing and services chronically homeless or non-chronical homeless? Second, when short-term housing assistance terminates, how to handle those exiting homeless so that they can quickly resettle into other available housing? Third, is it worthwhile to provide sustainable supports compared to temporary and relatively cheap short-term housing assistance?

Ironically, the corresponding housing inventory, such as transitional housing, for the applicants who encounter disabilities can only support less than 10 percent of the total chronically homeless. The homeless who use the rapid re-housing program are not counted as homeless. When they exit the RRH program, they still can't be self-independent. They end up sleeping on the streets because the current policy constrains them from applying for future homeless housing and services assistance. These circumstances can be modeled into the SD model in order to find out whether it affects homelessness.

The SD model is designed to mimic the empirical policies that are expected to mitigate homelessness crisis and the policies' operational process. The simulation model helps not only identify the unseen weakness that prevents homeless remedies from being effective, but also assess the impact of a new policy and its implementation on the overall homelessness.

The system dynamics model is implemented in Vensim PLE Plus.[14] In Vensim, a stock (level) presents a cumulative effect that occurs over time. A flow (the rate of change) represents the value change of the variable of interest at each time step or iteration. Figure 3-4-1 is the flowchart of the SD model's architecture. In this simplified flowchart, the three primary levels

[14] A System Dynamics modeling software. https://vensim.com/vensim-ple-plus/

are constructed based on the empirical evidence as discussed previously. They are as follows: (1) a homeless prevention system that aims to prevent extremely low-income population from becoming homeless; (2) short-term housing programs that aim to offer a place for the unsheltered homeless populations; (3) long-term housing and supportive housing that aim to facilitate the homeless to be self-sufficient.

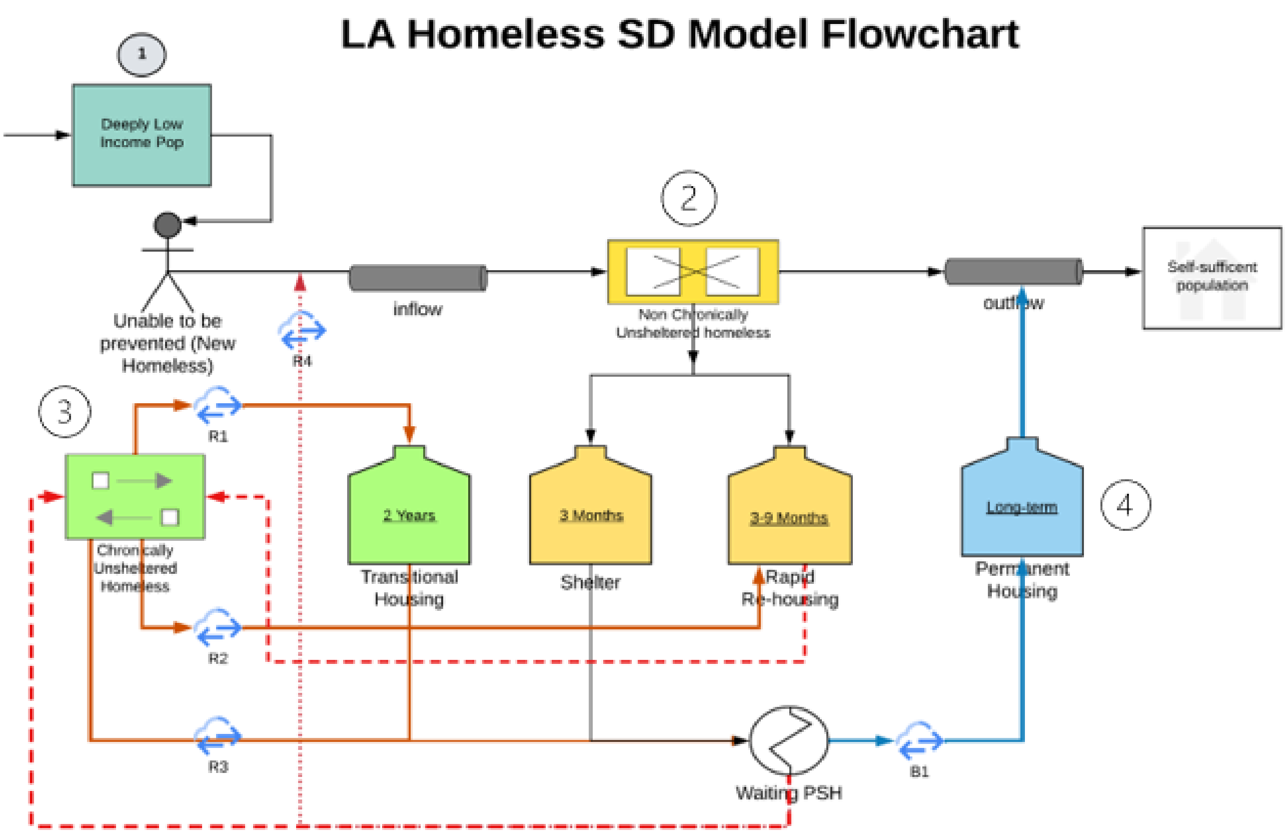


Figure 3-4-1. The Simplified System Dynamic Model Flowchart

It portrays three sublevels: a deeply low-income population in the homeless prevention level, the total unsheltered homeless population along with short-term housing programs (shelters, transitional housing, and rapid re-housing), and self-sufficient population in the long-term housing program. The simulation timespan is from 2008 to 2030, including a training period

(2008 to 2020) and a forecasting period (2021 to 2030). Each time step is set 0.25 year. The benchmark model generates 92 iterations or 23 years forecasts.

In Figure 3-4-1, from top left to bottom right, the first stock (Stock 1) aims to measure how many people from the deeply low-income population end up becoming homeless. Non-chronical homelessness (Stock 2) and Chronical homelessness (Stock 3) are two types of unsheltered homeless populations. They are modeled independently because the SD model is designed to examine whether two distinct groups should be served by different approaches. In the middle of the figure, between Stock 3 and 4, the first green "jar" is the transitional housing, which is directly connected with unsheltered chronically homeless. The second and third yellow "jars" after the transitional housing represent emergency shelters and the rapid re-housing program. Shelters are used as an urgent and temporary support for the non-chronically homeless, while the rapid re-housing can serve both two types of homeless people. Lastly, the homeless who are in a housing program may be transferred into a permanent supportive housing, Stock 4, where the long-term services and housing are offered. Among those who are served in the PSH program, few of them will return back to the streets (less than 5 percent become homeless again, HUD 2021) if the program consistently provides a full range of housing and health services.

A reinforcing loop (denoted by R) results in the increase of unsheltered homeless population; on the other hand, a balancing loop (denoted by B) leads to a decrease in unsheltered homeless population. In Figure 3-4-1, five primary feedback loops are identified. Four of them are reinforcing loops, meaning an increase of users in a housing program leads to an increase in homeless returns.

R1 in Figure 3-4-1 represents a reinforcing loop from chronically unsheltered homeless from the street to staying in the transitional housing, then from exiting the TH program and becoming chronically homeless again. It is identified as a causal loop between the TH program and the unsheltered homeless. Ideally, the homeless in the TH program should be self-sufficient right after the homeless' contract of staying in TH terminates. However, the reality is that the homeless is not able to be self-supported and since there is no other place for them to live, they live on the streets again.

R2 represents a reinforcing loop starting by the chronically unsheltered homeless from the street to the rapid rehousing, then become chronically homeless again when they cannot apply for any permanent supportive housing because they are not able to be self-sufficient when they exit the RRH program. There are two major differences between the TH program and the RRH program. First, the TH program can be as long as two years, while the RRH program on average is a 3-month program. Second, the TH provides not only housing for the chronically homeless, but also needed health services to keep the homeless person in the program. The RRH only provides short-term rental subsidies with limited or no supportive services even though the RRH can serve any type of homeless. In the reality, since the homeless are unlikely to be self-efficient in 3 months, they either find another place to stay or return back to the streets. This reinforcing loop creates a cumulative effect that piles up the total unsheltered homeless population over time, even remaining the new homeless input constant.

R3 represents the returned chronically homeless when they are waiting for the permanent supportive housing after they exit transitional housing. Ideally, the homeless who can't be self-independent continued being supported by the government assistance. In fact, there is a proportion of the homeless becoming returning homeless because they are living on the street while waiting for the permanent supportive housing.

R4 stands for the returning non-chronically homeless who are experiencing homeless for the first time due to unexpected circumstances. The new first-time homeless either choose shelter or rapid re-housing and during the waiting time for permanent supportive housing or they are not willing to use any housing services, they return to the streets if they don't have other places to stay. The non-chronical homeless population is the source of new homeless inputs.

In the current homeless housing system, one major balancing loop that can reduce homeless population is B1. In Figure 3-1-4, B1 is the loop that links those who are successfully housed in the PSH programs with the non-homeless population. The chronically and non-chronically homeless who are able to use the permanent supportive housing assistance and be supported by social services contribute to homeless population reduction. In addition, the homeless who temporarily settled in the RRH program are part of non-homeless population, but this non-homeless status disappears when they exit the program.

To summarize this section, the SD model is built in a way that aims to capture the key causal loops that cause or reduce homelessness based on the evidence collected from the empirical world. Returning unsheltered homeless population increases after people exit the short-term programs either because of their personal unwillingness of using social services or due to the unavailability of long-term supportive services.

3.4.1 Homeless Prevention Subsystem

A homeless prevention program aims to reduce the possibilities of being homeless by using subsidies to pay a proportion of rentals, utility bills, or mortgages. The expected targets at this level are the most vulnerable people in terms of facing severe financial difficulties which might cause eviction from current residentials and those who have a chronical disability which prevents them from being employed and therefore cannot be self-supported.

The grant for homeless prevention is pulled from HUD's ESG program. It is a small percentage of total homeless grants compared to the grant for CoC program, which is long-term housing-based project. According to HUD, 10 percent of the total homeless grant (2.7 billion dollars in 2021-22) are used for prevention, the rapid re-housing, and shelter along with supportive services. According to California Housing Partnership (2019), there are 1,236,778 deeply low-income[15] renter households who do not have access to an affordable home. Even though, a small proportion of deeply low-income population may end up being homeless, this group of people in the SD model is considered as the target population for the city to prevent becoming homeless.

To test the impact of the homeless prevention on homeless population, the target population for homelessness prevention is the deeply low-income individuals. This group of people is modeled as a stock or a level variable in the homelessness prevention subsystem. This stock connects two pipes or flows: a new homelessness increase rate and a homelessness prevention rate. The homeless prevention rate aims to measure the strength of housing subsidization on the deeply low-income individuals. Figure 3-4-1-1. below demonstrates a simplified structure on the prevention level in the system.

[15] Deeply low-income households (ELI), those incomes are at or below the poverty guideline or 30 percent of their area median income (AMI). Many of these households are severely cost burdened, spending more than half of their income on housing. https://nlihc.org/housing-needs-by-state/california

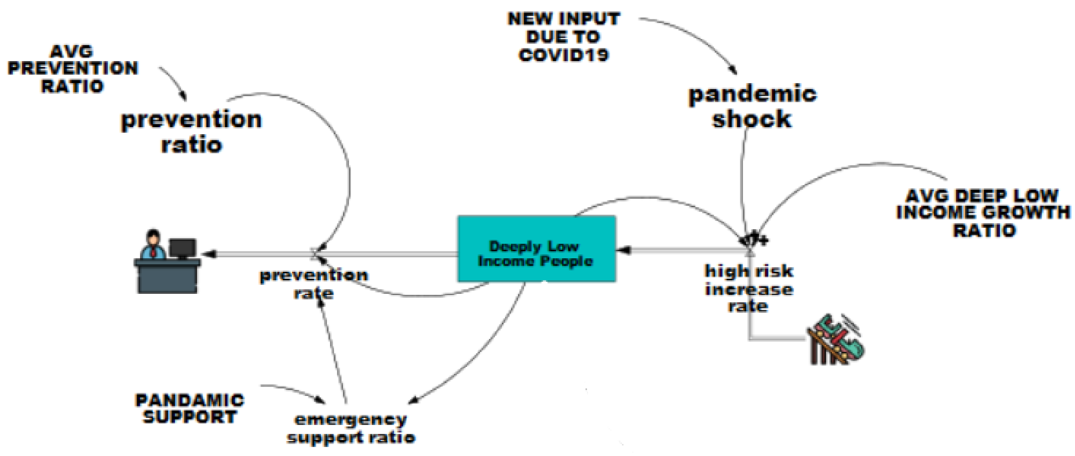


Figure 3-4-1-1. Simplified Homelessness Prevention Subsystem. The high-risk population is the deeply low-income individuals and this variable is modeled as a stock, named Deeply Low-Income People. The prevention ratio is the fraction of the total participants who are not homeless people to the total deeply low-income population. The high-risk increase rate (the in-flow of Deeply Low Income People) is affected by the average deep low income population growth ratio (AVG DEEP LOW INCOME GROWTH RATIO) and the one-time shock (pandemic shock).

In this subsystem, two primary causal loops are identified. One is the balancing loop and the other one is reinforcing loop. Figure 3-4-1-2 demonstrates the causal relationships using casual loop diagram (CLD).

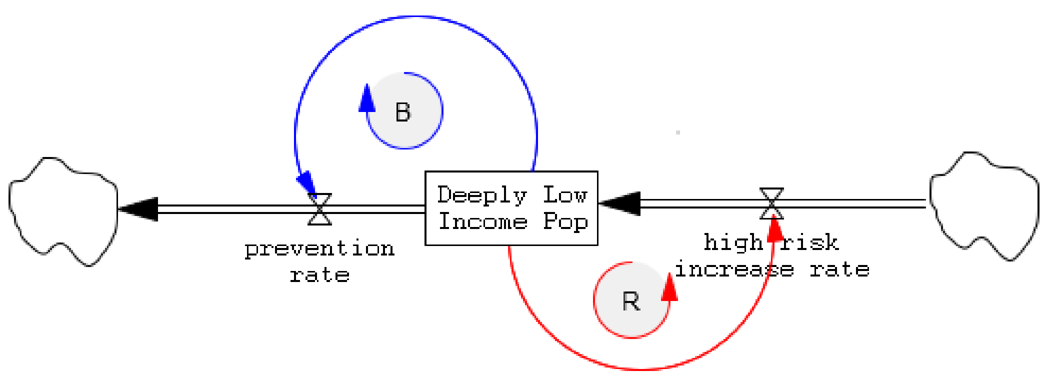


Figure 3-4-1-2. Casual Loop Diagram in Homeless Prevention Subsystem.

In Figure 3-4-1-2, the stock is the deeply low-income population. The stock connects two pipes. In system dynamics modeling, the pipes represent flows with directions. A pipe with an arrow pointing to the stock is called in-flow, it is an out-flow otherwise. In Figure 3-4-1-2, the pipe on the right side of the stock is an in-flow pipe. It results in the value of the stock increase over each time step. The pipe on the left side of the stock, however, is an out-flow pipe. This out-flow pipe leads to the value of the stock decrease over each time step.

The integration equation (1.1) below is applied for computing the prevented population.

$$\text{DLI Pop} = \int_0^n \Delta(DLI\ Pop) \cdot d(t) + DLI\ Pop_{(t=0)}. \tag{1.1}$$

- n stands for the number of iterations that the model conducts. It equals 92 (23 years multiplies 4-time steps in each year).
- DLI Pop stands for the deeply low-income individuals.
- $\Delta(DLI\ Pop)\ is\ the\ differnece\ between\ the\ inflow\ and\ outflow\ population.$
- $d(t)$ is the time step and it equals 0.25 (year).
- $DLI\ Pop_{(t=0)}\ is\ the\ intial\ value. It\ is\ the\ deeply\ low\ income\ population\ in\ 2008.$

Alternatively, the integral equation is denoted by:

$$Deeply\ Low\ Income\ People_t$$

$$= \int_{2008}^{2030} (\ high\ risk\ increase\ rate - prevention\ rate) \cdot 0.25$$

$$+ Deeply\ Low\ Income\ Pop\ _{(t=2008)}. \tag{1.2}$$

- $high\ risk\ increase\ rate =$

  $pandemic\ shock + AVG\ DEEP\ LOW\ INCOME\ GROWTH\ RATIO$

  $\cdot Deeply\ Low\ Income\ Pop. \tag{1.3}$

- *prevention ratio =*

total participants in prevention programs / total deeply low-income population. (1.4)

3.4.2 Housing Programs for the Non-Chronically Homeless

The housing subsystem comprises two major components: the housing programs for the non-chronically homeless and the housing programs for the chronically homeless. Most non-chronically homeless people stay at emergency shelters and wait for the opportunities of transferring to the permanent housing if the homeless individuals are qualified. The emergency shelters are the most common places for people who are facing homelessness for the first-time. Alternatively, the non-chronically homeless apply for the rapid rehousing and stay in the program for three months. Usually, the length of stay in the emergency shelter or rapid rehousing are equivalent. The RRH program, however, might extend longer if the funding is sufficient. For instance, in Malibu, a homeless person can stay in the RRH program up to 9 months.

Figure 3-4-2-1 portrays the key components and their relationships in the subsystem of the unsheltered non-chronically homelessness. The unsheltered non-chronically homeless is modeled as a stock. It connects two other stocks: one is the stock called Emergency Shelter (ES) and the other stock is called Rapid Re-housing. The ES stock connects an in-flow, which is a fractional ratio of sheltered homeless. This in-flow represents the percentage of the total sheltered homeless people to the total number of homeless people. The time factor which represents the waiting time for being sheltered (W TIME FOR ES) affects the velocity of the non-chronically homeless people to be sheltered. When the homeless people need to leave toward the end of stay in shelter, the sheltered homeless who still need supportive housing service, will apply for another housing programs, such as RRH or PSH, to stay. In other words, the shelter exit rate depends on the total sheltered homeless population, the length of stay in the ES, as well as the self-independence ratio for the homeless who use the service.

The other stock is the population who use the rapid re-housing program. Likewise, it depends on the waiting time for homeless people to be granted the use of the RRH program and the capability of the RRH. The RRH's capability is represented by a fractional rate of a net intake from the total non-chronically homeless. When the homeless people exit the RRH, they are expected to live on their own. But this expectation seems not realistic even for the non-chronically homeless. In fact, a 3-month RRH doesn't provide enough time for most homeless people to get a job in order to afford housing and living expense. Figure 3-4-2-1 is used for illustrating the relationship between the non-chronically homeless and the two short-term housing programs: the emergency shelter and the rapid re-housing.

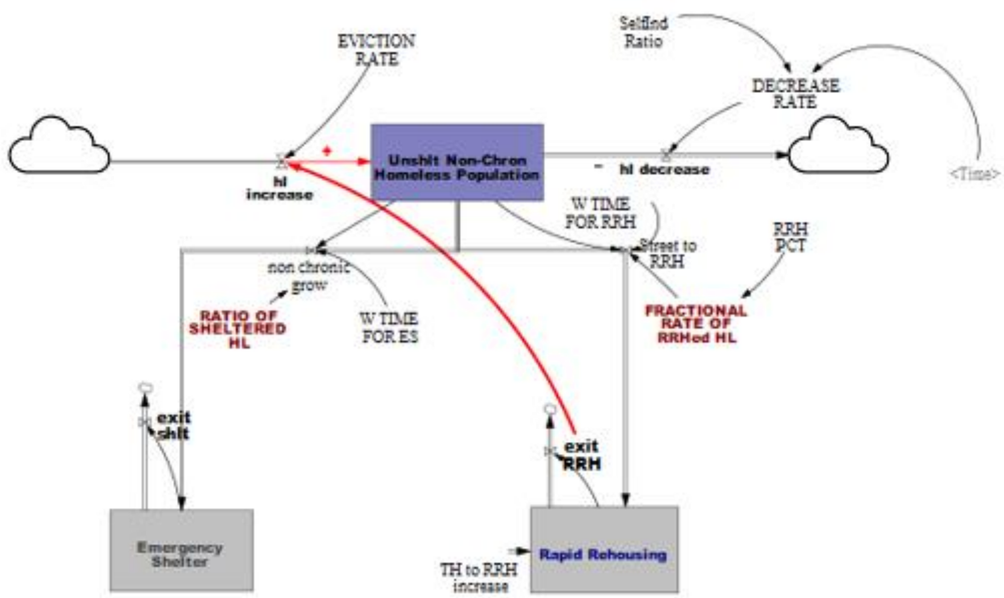


Figure 3-4-2-1. A Simplified Flowchart of the Short-Term Housing and the Chronical Homelessness

In this subsystem, the primary causal relationships are depicted by the causal loop diagram or CLD shown in Figure 3-4-2-2. The following equations 2.1-2.3 and 3.1-3.3 are the key mathematical functions involved in this subsystem.

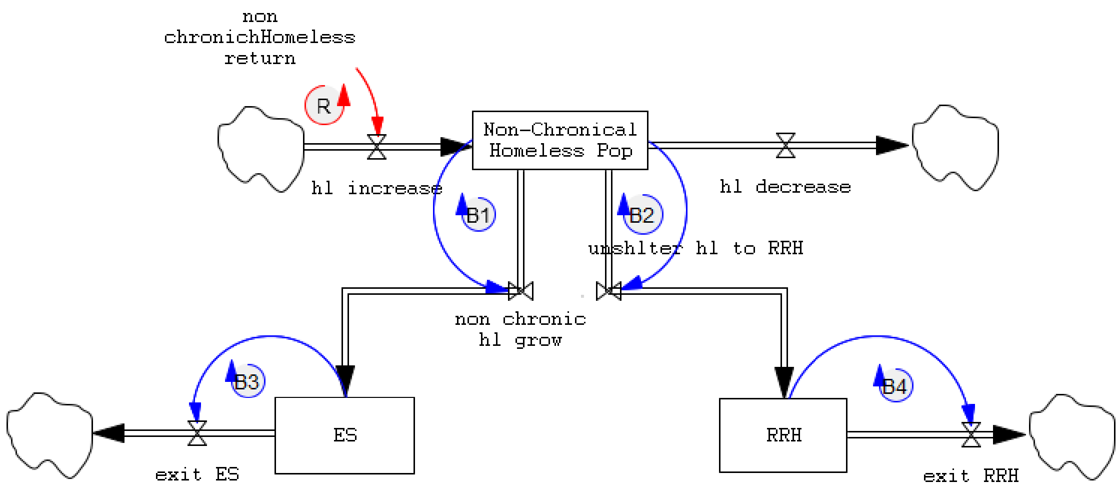


Figure 3-4-2-2. The CLD of the Non-Chronical Homeless Subsystem

Four dominate rebalancing loops with one primary reinforcing loop are identified and denoted by B1, B2, B3, B4, and R., respectively.

➢ ***Unsheltered Non-Chronical Homeless Population***

- $Unsheltered\ Non-Chronical\ Homeless\ Pop$

$$= \int_0^n (hl\ increase - hl\ decrease) \cdot d(t) + unsheltered\ HL\ Pop_{(t=0)}. \qquad (2.1)$$

Where the cumulative effect of the unsheltered non-chronically homeless population is calculated by integrating the sum of the difference between homeless increase (people/year) and homeless decrease (people/year) multiplying by each time step 0.25 (year) and the initial value of the unsheltered chronically homeless population (people) in 2008.

Sheltered Population

- $Emergency\ Shelter_t =$

$$\int_0^n (non\ chronic\ grow - Exit\ ES) \cdot d(t) + ES_{(t=0)}. \qquad (2.2)$$

Where the cumulative effect of the sheltered population is calculated by integrating the sum of the difference between non-chronically homeless population grow rate (people/year) and the homeless exiting ES rate (people/year) multiplying by each time step 0.25 (year) and the initial value of the sheltered homeless population (people) in 2008.

- $non\ chronic\ grow_t$

$$= d(\frac{Unshlt\ Homeless\ Pop_{(t)}}{W\ TIME\ FOR\ ES} \cdot\ RATIO\ OF\ SHELTERED\ HL\ ) / \triangle t. \qquad (2.3)$$

The first order of derivative is used to compute the rate of change in non-chronically homeless growth at each time step. The non-chronically homeless growth rate (people/year) is the rate of total unsheltered non-chronical homeless population (people) at a given time multiplying by the average homeless shelter percentage (percentage) then divided by the waiting time for the homeless to be sheltered (year).

- $exit\ shelter_t = d(\frac{the\ Sheltered\ Homeless_{(t)}}{DURATION\ IN\ SHELTER}) / \triangle t. \qquad (2.4)$

The exit shelter population is calculated by the first order of derivative of the sheltered homeless population (people) at a giving time step divided by the length of stay in the shelter (year).

➢ ***Rapid Re-housed Homeless Population***

- $Rapid\ Rehousing_t = \int_0^n (Enter\ RRH - Exit\ RRH) \cdot d(t) + \ RRH_{(t=0)}. \qquad (3.1)$

The population in the rapid rehousing program is an integration of the summation of the difference between the homeless who enter the RRH and those who exit the program at each time step and the initial homeless population in the program in 2013.

- $\boldsymbol{Unsheltered\ to\ RRH_t} =$

$$d\left(RATIO\ OF\ RRHED\ HL\ \cdot \frac{Unsheltered\ non\text{-}chronic\ Homeless\ Population_{(t)}}{W\ TIME\ FOR\ RRH}\right)/\triangle t. \tag{3.2}$$

The increased unsheltered homeless rate from RRH (people/year) is computed by the first order of derivative of the unsheltered non-chronically homeless (people) at a given time step multiplying the RRH percent and then divided by the waiting time (year) for the RRH program.

$$exit\ RRH_t = d\left(\frac{Rapid\ Rehoused\ Population_{(t)}}{DURATION\ IN\ RAPID\ REHOUSING}\right) / \triangle t. \tag{3.3}$$

The homeless exiting RRH rate (people/year) is calculated through the first order of derivative of the rapid rehoused population (people) at a given time step divided by the length of stay in the program.

3.4.3 Housing Programs for the Chronically Homeless People

People who don't qualify for shelters may qualify for transitional housing. Generally, the transitional housing is for chronically homeless who have disabilities, either mentally or physically. Unlike other short-term housing programs for the non-chronically homeless people, the TH is a 2-year temporary housing solution combined with health supportive services. The chronically homeless people stay in TH up to two years, then are expected to move into a permanent supportive housing. Another commonly used short-term housing for the chronically homeless people is rapid re-housing. RRH was first offered in 2013. Ideally, the homeless can be integrated into either the RRH or the PSH after they exit from TH. The causal relationships involved in this subcomponent are illustrated in Figure 3-4-3-1 and Figure 3-4-3-2.

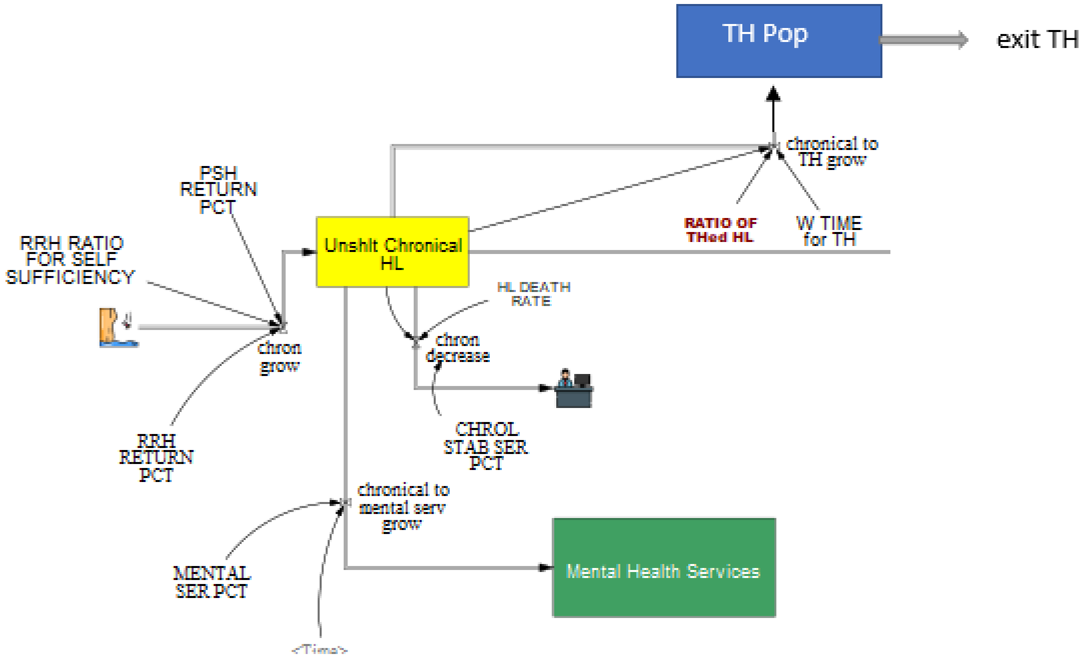


Figure 3-4-3-1. A Simplified Flowchart of the Short-Term Housing and the Chronically Homeless

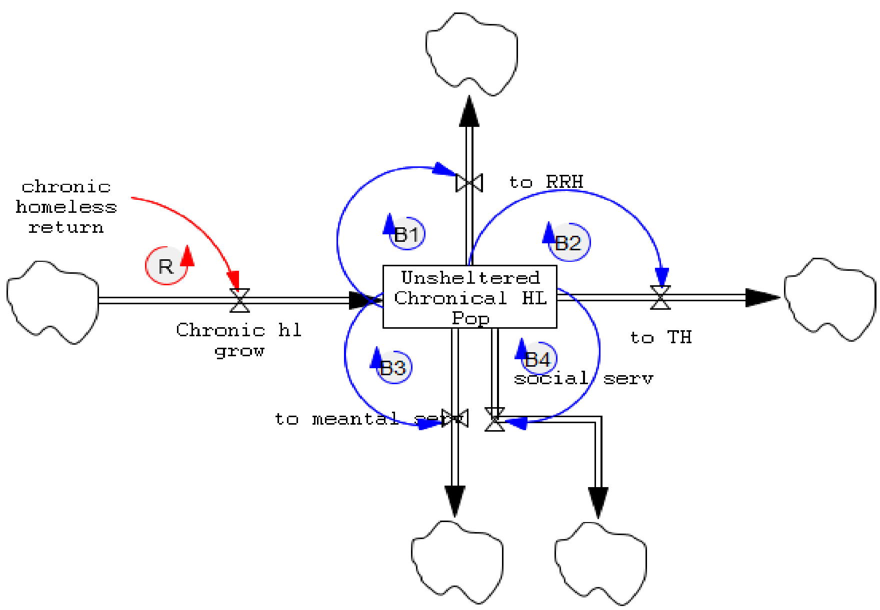


Figure 3-4-3-2. The CLD of Chronically Homeless Subsystem

In this subcomponent, four rebalancing loops and one primary reinforcing loop are identified:

B1: Moving the chronically homeless to the RRH program leads to a decrease in unsheltered chronically homeless population.

B2: Moving the chronically homeless to the TH program leads to a decrease in unsheltered chronically homeless population.

B3: Helping the chronically homeless to get mental health service leads to a decrease in unsheltered homelessness.

B4: Facilitating the chronically homeless to get social services leads to a decrease in unsheltered homelessness.

R: The returning chronically homeless have a positive impact on unsheltered homelessness.

The important equations involved in this subcomponent are as follows:

- ***Population in Transitional Housing***

- $TH\ Pop_t = \int_0^n (chronical\ to\ TH\ grow - exit\ TH) \cdot d(t) + TH_{(t=0)}$. (4.1)

The homeless who use the TH at a given time is the integration of the summation of the difference between the TH program growth rate (people/year) and the TH exit rate (people/year) multiplying each time step 0.25 (year), and the initial population in the TH program in 2008.

- ***Unsheltered Chronically Homeless Population***

- $Unshlt\ Chronical\ HL_t = \int_0^n (chrongrow - chronical\ to\ TH\ grow - chron\ decrease) \cdot d(t) + Unshlt\ Chronical\ HL_{(t=0)}$. (4.2)

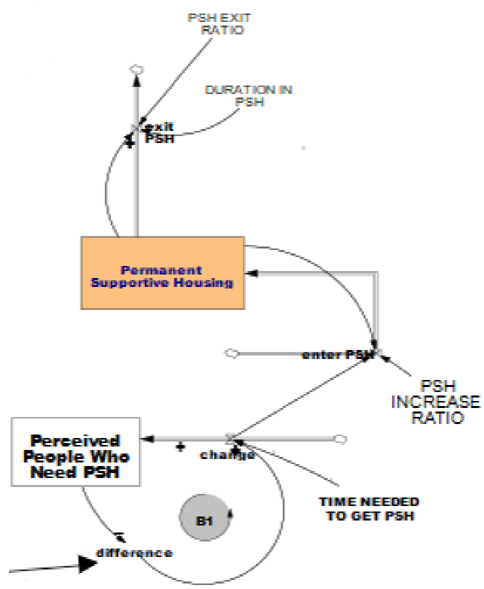
The unsheltered chronically homeless at a given time is the integration of the difference between chronically homeless growth (people/year) and the growth rate for the chronical homeless who are in the TH program (people/year) multiplying by each time step, and the initial unsheltered chronical homeless in 2008.

- ***Population in Health Services***
  - $Mental\ Health\ Served\ Pop_t = \int_0^n (chronical\ to\ mental\ serv\ grow) \cdot d(t) + Mental\ Health\ \ Served\ Pop_{(t=0)}$. (4.3)

The population in the mental health facilities is the integration of the summation of the mental services receiver growth rate (people/year) multiplying by each time step and the initial population that is served in 2020. Note that this variable is designed and used only for the simulation procedure. It helps to find out the best policy that can effectively reduce homeless population. In reality, there is not such mental service provided, and this could be why the Housing First policy is ineffective in combatting homelessness in Los Angeles.

3.4.4 The Permanent Supportive Housing

The Housing-First policy consists of Rapid Re-housing and the Permanent Supportive Housing. Compared to RRH, the Permanent Supportive Housing program can be a long-term housing program. PSH aims to provide the homeless not only a place to live but also supportive services, such as mental health care, drug and alcohol rehabilitations, education programs and job training. Figure 3-4-4-1 below depicts a simplified framework of the PSH. Figure 3-4-4-2 depicts a CLD in this subcomponent.



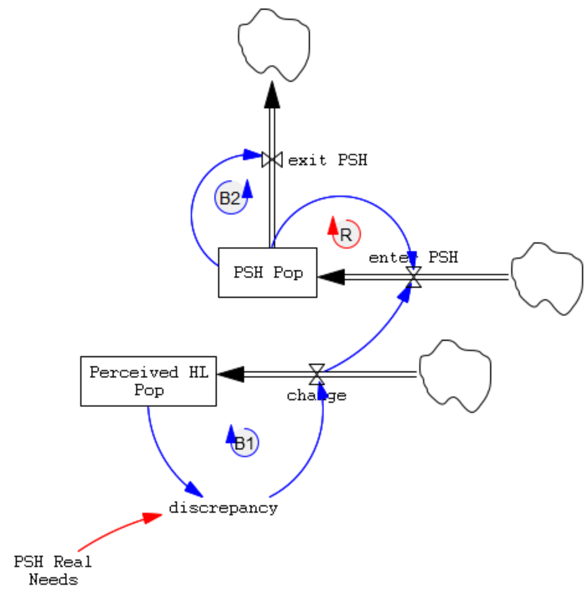


Figure 3-4-4-1 (Left). The Permanent Supportive Housing Flowchart

Figure 3-4-4-2 (Right). CDL of the PSH Subcomponent in the SD System

Two rebalancing loops mitigating the burden of the stocks for the PSH and one reinforcing loop of increase the needs in the PSH are found:

- B1: The actual needs for the PSH are unknow until the volunteers count them on a given day in January very two years. This unknown number results in an increase in the discrepancy between the actual homeless who need PSH and the housing provider's perception.
- B2: If the homeless people become self-sufficient, then the PSH population decreases.
- R: An increase in the PSH growth rate leads to an increase in the PSH population.

In this long-term housing subcomponent, there is a conceptional stock in B1,reflecting the policy maker's perception about the reality. The perception stock is critical as it reveals a goal seeking behavior. The goal seeking behavior is produced by the discrepancy between human's expectation and the reality over time. The Perceived People Who Need PSH mirrors LA policy maker's estimated homelessness. It takes time for the policy makers to know what is going on because it is difficult to know accurate homeless head accounts when the homeless move around from one place to another. Due to the pandemic, the annual homeless point-in-time head count activity in 2021 was cancelled. If it was not, it would still take a year for the policy makers to know the homeless status. However, one remedy of it is to have homeless outreach social workers inspect and look for the homeless in their managed territory on a regular basis. Using a GIS app such as Survey 123, for example, the social work and homeless solution staffs in the City of Riverside immediately locate the homeless and share their location with the City's administrative team.

In this subsystem, the following equations are applied to simulate the outcomes of the interest.

Permanent Supportive Homeless Population

- $Perceived\ People\ Who\ Need\ PSH$

$$= \int_0^n (change) \cdot d(t) + Perceived\ People\ Who\ Need\ PSH_{(t=0)}. \quad (5.1)$$

The perceived population for PSH is the integration of the summation of the change rate (people/year), affected by the discrepancy, multiplying by a time step, and the initial perceived population for the PSH in 2008.

- $PSH_t = \int_0^n (enter\ PSH - exit\ PSH) \cdot d(t) + PSH_{(t=0)}. \quad (5.2)$

The population in the PSH in a given time is the integration of the summation of the difference between the PSH input growth rate (people/year) and the PSH exit rate (people/year) multiplying by a time step 0.25 (year), and the initial population in the PSH program in 2008.

- $difference_t = d(PSH\ Demand - Perceived\ PEople\ Who\ Need\ PSH)$ / $\triangle$t. (5.3)

The difference is the first derivative of the discrepancy which is computed by the difference between the real PSH demand and the perceived PSH demand.

- $change_t = d\left(\frac{Perceived\ People\ Who\ Need\ PSH}{TIME\ NEEDED\ TO\ GET\ PSH}\right)/\triangle t.$ (5.4)

The change in the PSH demand at each time step is the first order derivative of the perceived PSH demand divided by the time needed to know such demand.

In this section, the key components for homeless housing and services are displayed independently. The key mathematical equations are briefly introduced. A more detailed description of the equations and initialization setup can be found in Appendix B.

3.4.5 Vensim Embedded Function

Considering the existence of time delays at any given levels, the build-in DELAY function and STEP function are employed. The delay functions are used when computing the increase and decrease of the homeless population for the following reasons. (1) It takes one year for the homeless to be qualified as chronically homeless. In other words, the homeless are not qualified to be housed by PSH unless they have been homeless for at least one year. (2) The homeless usually stay in a temporary housing program for a few months before moving into a permanent program. The length of stay in the short-term housing program is the “delay” time of the homeless in the housing program before moving into another place. The delay function is critical in the SD model. Delay causes fluctuate behavior on the macro level. In this SD model, for example, the PSH population growth rate equals the derivative of the total PSH demand divided by the needed time to be settled into the PSH. The denominator of the waiting time creates nonlinear behaviors for the population in PSH programs. The more delay variables involved the more oscillating behaviors in the PSH population observed.

Another function widely used in the model is STEP function. The STEP function is used for the RRH stock and Prevention stock since RRH did not exist until 2013 and the prevention program was not implemented until 2018. The STEP function allows the new attribute to be active at particular time points across simulations.

The IF THEN ELSE function aims to set a condition when there is not sufficient PSH inventory for all the applicants. It means if there are enough permanent supportive beds and those who are waiting on permanent places are qualified, all of them will be successfully stabilized by the PSH program. Otherwise, some who are not able to be settled in the PSH program return to the streets.

In this section, the SD framework is introduced first, followed by breaking down the whole system into three primary subcomponents. The three key subcomponents are elaborated with details in order to understand the homelessness system and the causal. Lastly, the homelessness system is shown in Figure 3-4-5.

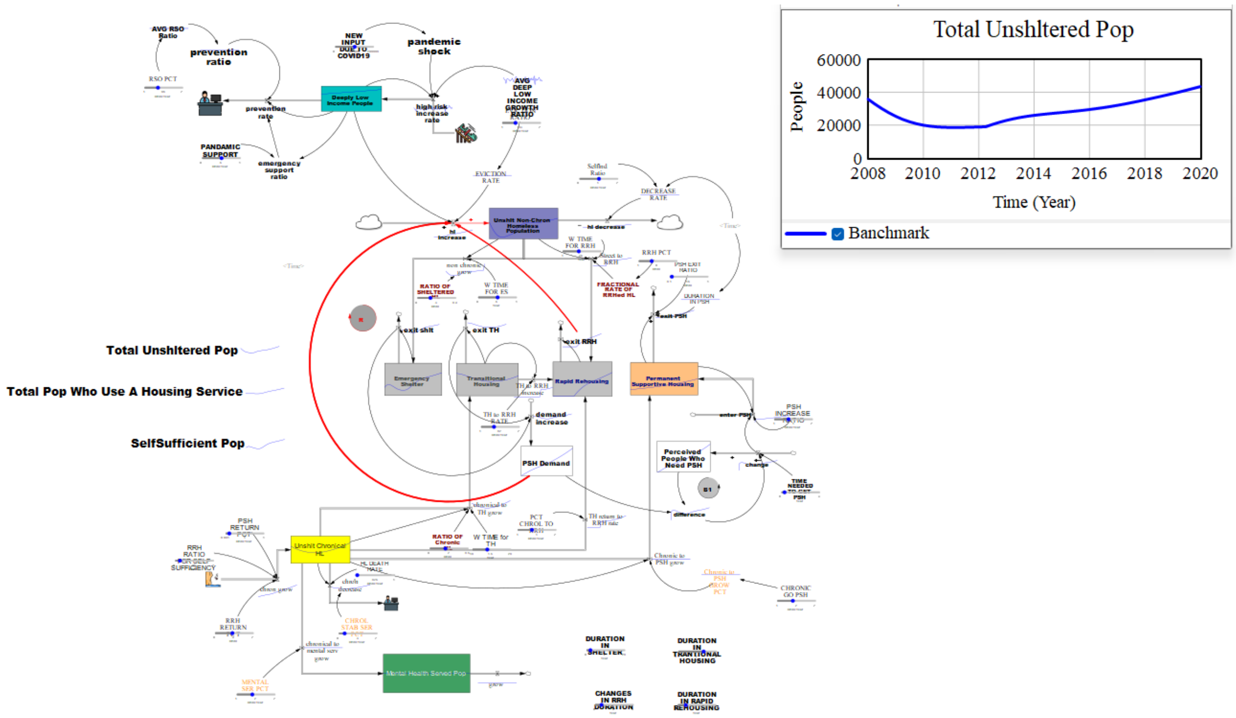


Figure 3-4-5. A Snapshot of a single run based on the Benchmark Model Setup in Vensim PLE plus[16]

[16] Vensim PLE Plus, vensim.com

Chapter 4

System Dynamics Model Simulation

4.1 Parameter Initialization and Model Validation

An annual population dataset for homeless housing inventory and homeless population headcounts was pulled from HUD-Exchange.[17] The unit of analysis is CoC participants at county/city level. The dataset includes information for homeless housing inventory and point-in-time (PIT) homeless headcount between 2007 and 2020. The data frame of the sample is a cross-sectional time series data frame. The finalized sample data is created by merging housing inventory count data (HIC) into homeless population point-in-time headcount data set (PIT) using the key index of CoC IDs. All the parameters need to be initialized by either empirical reported data or simulated data, depending on the data availability and data validity. Appendix B lists details for parameter's initializations of Los Angeles homelessness system dynamics model.

To evaluate model quality, the first validation test is to get units checked. In the system dynamics model, every variable should have a unit. For example, the unit for the stock of unsheltered homeless population is people. The unit for a rate or inflow/outflow of homelessness is people per year. A unit for a constant, such as annual percentage of sheltered homeless people is a decimal/fraction. It is vital for the SD model to have units correctly mapped based on the mathematical equations. Unit check is also the simplest way to identify errors that make no logical sense. In the homelessness model, all variables' units are consistent, so the model has passed one fundamental validation test. Second, the model's Delta T by default is set 0.25 timestep. A large

[17] PIT and HIC Data Since 2007 - HUD Exchange

Delta T might cause calculation errors, while a too small Delta T will slow down the simulation even through the Delta T doesn't carry any real world meaning. Rather, it is for calculation accuracy only. The default time step 0.25 in this model seems appropriate as the model does not require either huge simulation iterations or data inputs. Third, since the model structure is evaluated by the homeless manager of Malibu, LA county, all the variable names carry real world meanings. In addition, the simulated population output is not below zero throughout all iterations. It indicates the model does what it supposes to do. The last test before running into scenario analysis is to perform a behavior reproduction test. To do so, the simulated outputs are compared with the empirical data. Figure 4-1 below displays the comparison results on the total unsheltered homeless populations between empirical records and the simulated outcomes.

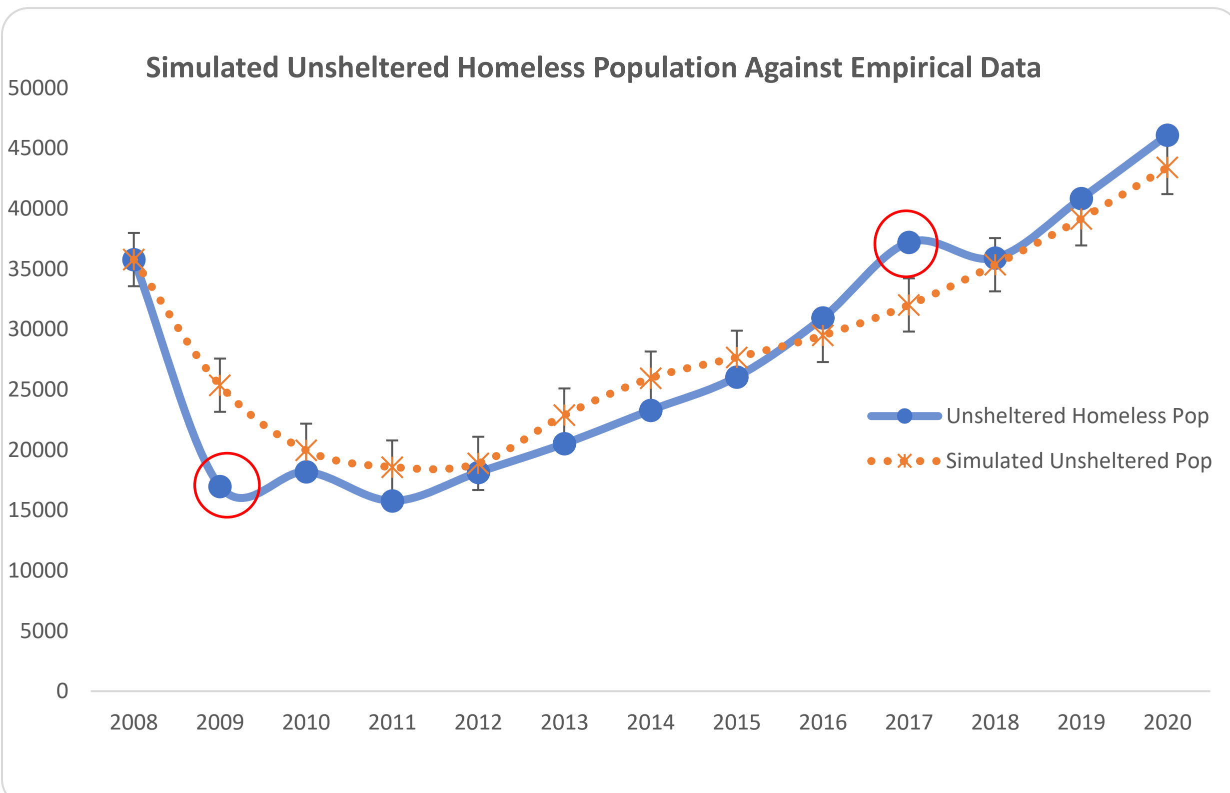


Figure 4-1. The Comparison Graph Between Simulation Data and Empirical Data

The SD model's overall behaviors are prima facie valid as the simulated results qualitatively mirror the empirical data. The simulated data points from 2008 to 2020 fall into the standard error interval, excepting the value points in 2009 and 2017. The SD model's root of sum error ratio is 0.586 [18] and it's mean percentage error (MPE) is 6 [19]. Note that the empirical data for unsheltered homeless population in 2018, 2020, and 2012 are not avaiable. These missing value points are replaced with the moving averages. Since the needed tests have been evaluated, based on the model's behavior performance, we can continue to conduct a global sensitivity analysis for testing whether the benchmark model can produce consistent simulation outcomes.

4.2 Sensitivity Analysis

4.2.1 Sensitivity Analysis Using Benchmark Model

The aim of performing global sensitive analysis is to test if the simulation model's outputs are reliable and how they can generate consistent results based on multivariate inputs. In this section, particularly, the following parameters are adjusted: (1) the eviction prevention ratio; (2) the length of stay in the rapid re-housing program; (3) the length of stay in the transitional housing program, and (4) the mental health services percentage. These are key policy levers in both the LA and general homelessness contexts. The prevention ratio aims to measure the impact of preventative programs on unsheltered homeless population, which is positively related to the total homeless population. The length of stay in the rapid re-housing program measures the impact of the short-term housing support unsheltered homeless returns. The length of stay in the transitional

[18] $Root\ of\ Sum\ Error\ Ratio = \sqrt{\sum(\frac{\varepsilon}{X})^2}$

[19] $Mean\ Percentage\ Error = 100(\frac{1}{n}\sum\frac{\varepsilon}{X})$

housing reflects the impact of a 2-year TH program on homelessness. The setup detail in Vensim PLE Plus is attached to Table 4-1 below.

Table 4-1. Parameter Setup for Multivariate Sensitivity Analysis (Global Sensitivity Analysis)

Parameter	Benchmark Model	Sensitivity Analysis Model Period: 2020 to 2030		
	Initial Value	Min	Max	Distribution
Avg. Eviction Prevent Rate	0.05	0.5	0.95	Uniform
RRH Length (year)	0.5	0.3	5	Uniform
TH Length(year)	2	1	3	Uniform
Mental Services %	0.2	0.1	0.5	Uniform
Social Services %	0.3	0.1	0.5	Uniform
RRH %	0.05	0.03	0.07	Uniform
TH to RRH %	0.02	0.02	0.5	Uniform
Chronic to PSH	0.5	0.5	0.9	Uniform
HL Growth Rate	0.02	0.005	0.02	Uniform

4.2.2 Multivariate Sensitivity Analysis Result

The simulation model iterates 200 times based on the different parameter inputs. Figure 4-2-1 presents the sensitivity result.

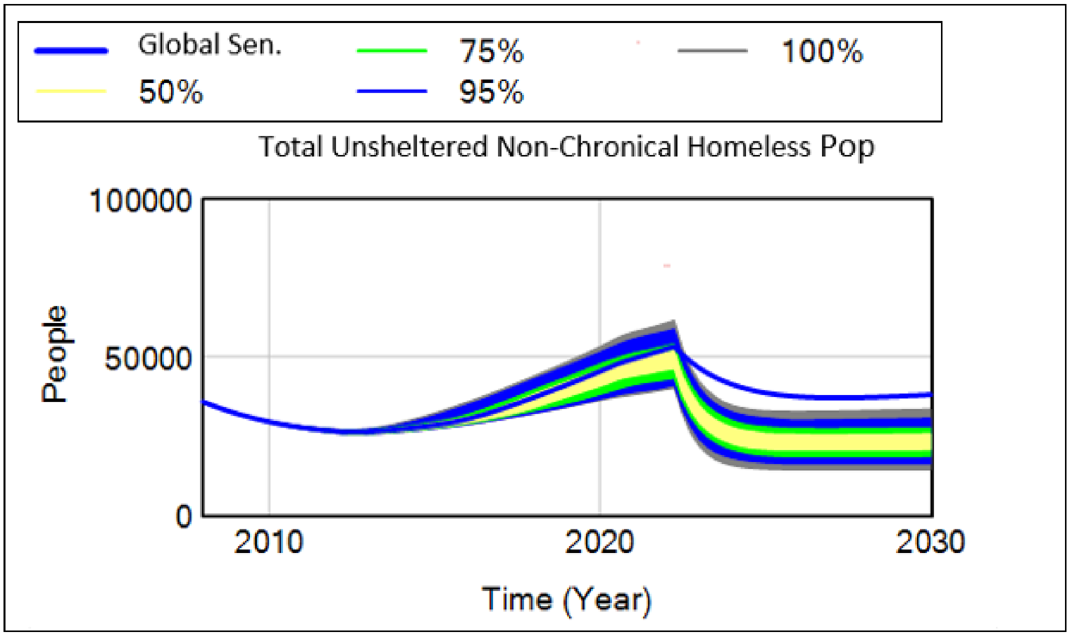


Figure 4-2-1. The Multivariate Sensitivity Analysis Based on the Benchmark Model

In Figure 4-2-1, the solid blue line labeled "Global Sen." stands for the simulation of the global sensitivity analysis. The two solid gray lines are the boundaries of all simulated data points for the total unsheltered non-chronically homeless population. For instance, the yellow ribbon means that 50 percent of the simulated value points falls into a bracket between 20,000 and 24,000 homeless people headcounts after 2022.

Based on the input setup in Table 4-1, the simulated results in Figure 4-2-1 display a decreasing trend after 2020 and reach an equilibrium around 25,000 estimated unsheltered homeless in 2030. The simulation outcome suggests that with an improvement in eviction prevention and direct use of permanent supportive housing programs, at a confident level of 95 percent, by 2030 the unsheltered homeless population would fall between 18,000 and 26,000. It also indicates that if LA's policy makers expect to reach zero-unsheltered homelessness, the prevention of the direct eviction and the implementation of direct transition from short-term housing to permanent supportive housing are the key focuses. Other factors, such as the rent stabilization ordinance, the length of stay in a short-term housing program and a long-term housing, and the supply of rapid re-housing inventory will be tested using scenario analysis in the next section of this chapter.

To look at a specific attribute and its impact on the unsheltered homeless, a heat map is created to understand a dynamic relationship between variables. Figure 4-2-2, for example, illustrates how the changes in eviction ratio and the PSH ratio affect the total unsheltered homeless population between 2021 and 2030.

	Eviction Ratio				
PSH Increase Ratio	0.01	0.015	0.02	0.025	0.03
0.1	18534	18900	19316	19775	20281
0.15	14360	14385	14433	14572	14787
0.2	12307	12310	12319	12343	12483
0.25	11496	11496	11500	11513	11618
0.3	10990	10990	10990	11000	11076

◉ Top 10
○ Bottom 10

	Eviction Ratio				
PSH Increase Ratio	0.01	0.015	0.02	0.025	0.03
0.1	18534	18900	19316	19775	20281
0.15	14360	14385	14433	14572	14787
0.2	12307	12310	12319	12343	12483
0.25	11496	11496	11500	11513	11618
0.3	10990	10990	10990	11000	11076

○ Top 10
◉ Bottom 10

Figure 4-2-2. A Heat Map of Total Unsheltered Homeless Population Based on Eviction and PSH Ratio

The heat map suggests that between 2021 and 2030 the higher eviction ratio combined with a lower PSH housing ratio (eviction ratio is 0.03 and PSH ratio is 0.1) leads to a higher unsheltered homeless population (20,280 homeless persons in the top 10 highest unsheltered homeless population table). In contrast, a lower eviction ratio along with a higher PSH housing ratio (eviction ratio is 0.01 and PSH ratio is 0.15) has a positive impact on homeless mitigation (14,360 homeless persons in the bottom 10 lowest unsheltered homeless population table).

The SD model of LA homelessness depicts one important characteristic: resilience. The system itself is able to adopt and adapt to the unexpected changes. In this analysis, after 2020, the system is forced to update their parameters under a relatively better conditions, but the model's simulation outcomes suggest that the system's balancing loop eventually stops unlimited decline in the unsheltered homeless population. Therefore, in the following sections, scenario analysis is used to find out if there is an actionable and more effective solution for Los Angeles not to have any unsheltered homeless.

4.3 Scenario Analysis of Potential Los Angeles Policies

In the previous section, the OLS regression model infers that the rent stabilization ordinance is positively and statistically significantly associated with unsheltered homeless population decrease. There were about 3,511 mentally ill homeless people discharged from LA county jail in 2018. Discharged homeless people usually end up sleeping on the streets. The discharged homeless people and the evicted people from residents comprise a proportion of new homelessness inputs.

In the following session, two primary policy levers, rent stabilization ordinance unit occupation ratio and eviction including discharged homeless people from jail, are tested.

4.3.1 Scenario I Homeless Prevention - Rent Stabilization Ordinance

The goal of this scenario is to understand the impact of RSO users on the total homeless population between 2021 and 2030. To do so, first, the average rent-controlled housing coverage ratio is increased from 0.05 to 0.2, leaving other control variables unchanged. Second, the ratio is increased from 0.2 to 0.9, leaving other control variables unchanged. In other words, we would like to see the impact of 4 times and 9 times the current RSO coverage ratio on homelessness. Figure 4-3-1-1 shows output comparison between different RSO ratios.

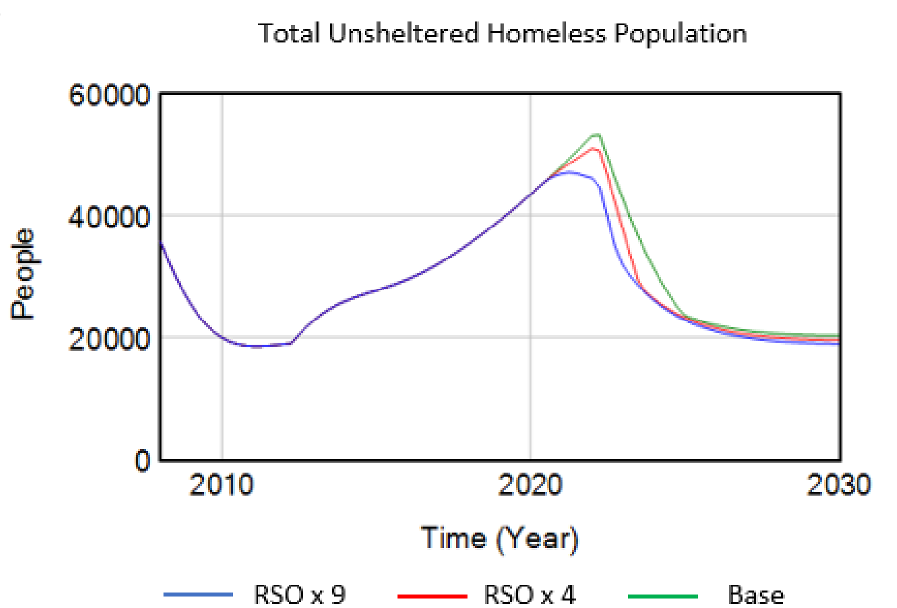


Figure 4-3-1-1. Simulated Results for Adjusted Rent-Controlled Housing Occupation Ratio After 2020

Note that a large increase in the rent stabilization housing occupation ratio leads to a decrease in the unsheltered homeless population (the red and blue line after 2020). The simulation result indicates the RSO has an impact on homeless mitigation. However, RSO seems insignificant on overall unsheltered homelessness. Let's look at how RSO unit occupation ratio affects non-chronical homelessness. Figure 4-3-1-2 shows the result of simulated non-chronically homeless population based on the same parameter setup.

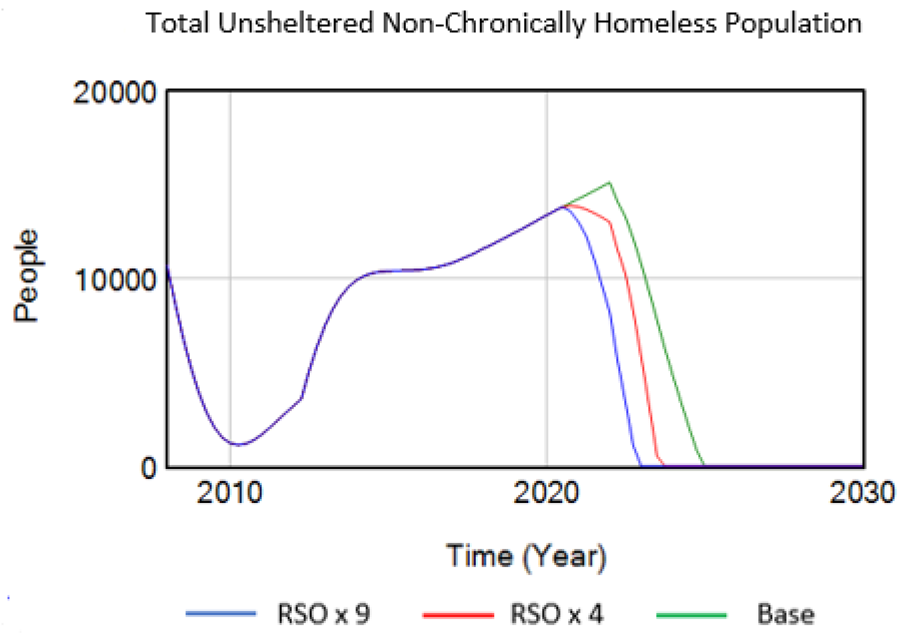


Figure 4-3-1-2. The Impact of RSO Occupied Unites Ratio on Unsheltered Non-chronically Homeless

The simulated result suggests that on average, a 4-time RSO occupation ratio leads to around 1,400 decreases in unsheltered non-chronically homeless people every year. Alternatively, a 10-time RSO ratio leads to an annual decrease of 3,029 unsheltered non-chronically homeless people. The simulations indicate that RSO occupation ratio has more impact on non-chronically homelessness but not much on the chronically homelessness. This finding is also supported by the OLS regression model.

4.3.2 Scenario II Homeless Prevention - Eviction

Eviction is a driver of homelessness growth, and this assumption is also supported by the OLS regression. To evaluate the strength of eviction on the total unsheltered homeless, the eviction percentage of the total deeply low-income people is first decreased from 0.03 to 0.025, then increased to 0.035. The simulation results are displayed in Figure 4-3-2-1.

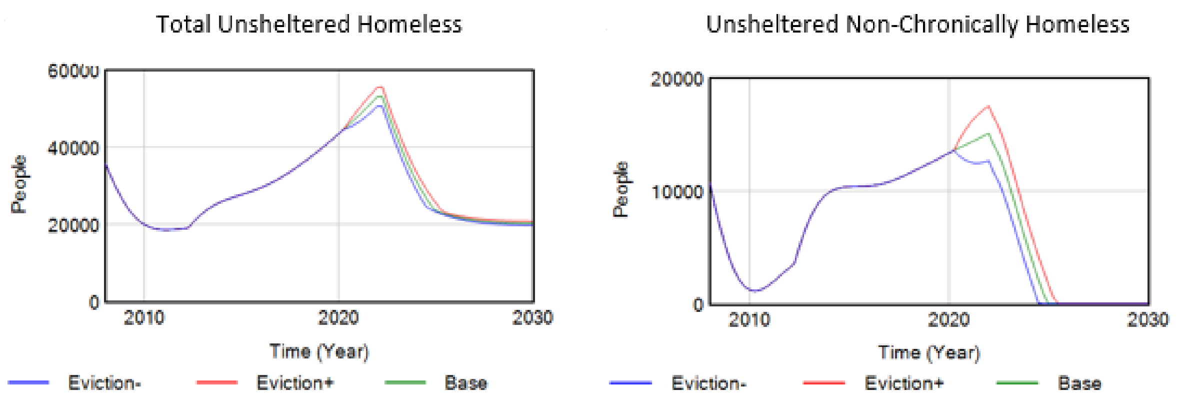


Figure 4-3-2-1(left and right). The Simulation Outcomes based on Changes in the Eviction Fractional Rate

The simulation outcomes indicate the eviction ratio has a positive effect on the unsheltered non-chronically homeless increase. On average, a 0.5 percent decrease in eviction ratio leads to 1,992 decreases in non-chronically homeless. Eviction, however, seems not to affect much on chronically homeless population.

4.3.3 Scenario III Rapid Re-housing

The rapid re-housing program is one component of the Housing First policy. It aims at providing individuals and families experiencing homelessness with time-limited rental subsidies and supportive services, enabling them to quickly secure housing and pay their rent until they are able to cover the costs on their own. [20] The challenge is that whether the RRH approach effectively solves Los Angeles homelessness, since the more people using the RRH the more homeless return to the streets after exiting the program. Therefore, in the following section, the RRH is tested from the following perspectives: (1) the RRH's capacity (FRACTIONAL RATE OF RRHed HL), and (2) the RRH's length of stay (DURATIONIN IN RAPID REHOUSING).

4.3.3.1 Rapid Re-housing Supply

The difference between an increase and a decrease of the percentage of the RRH capacity is assessed. Figure 4-3-3-1 shows the simulation outcomes when the fractional rate of the homeless using RRH is increased from 0.05 to 0.3, then decreased to 0.01, holding other variables constant. In other words, we would like to test the impacts of RRH program on homelessness by increasing RRH bed inventory and admission rate by 6 times and decreasing RRH bed inventory and admission rate by 5 times.

[20]County of Los Angeles, https://data.lacounty.gov/stories/s/a5c7-aawq

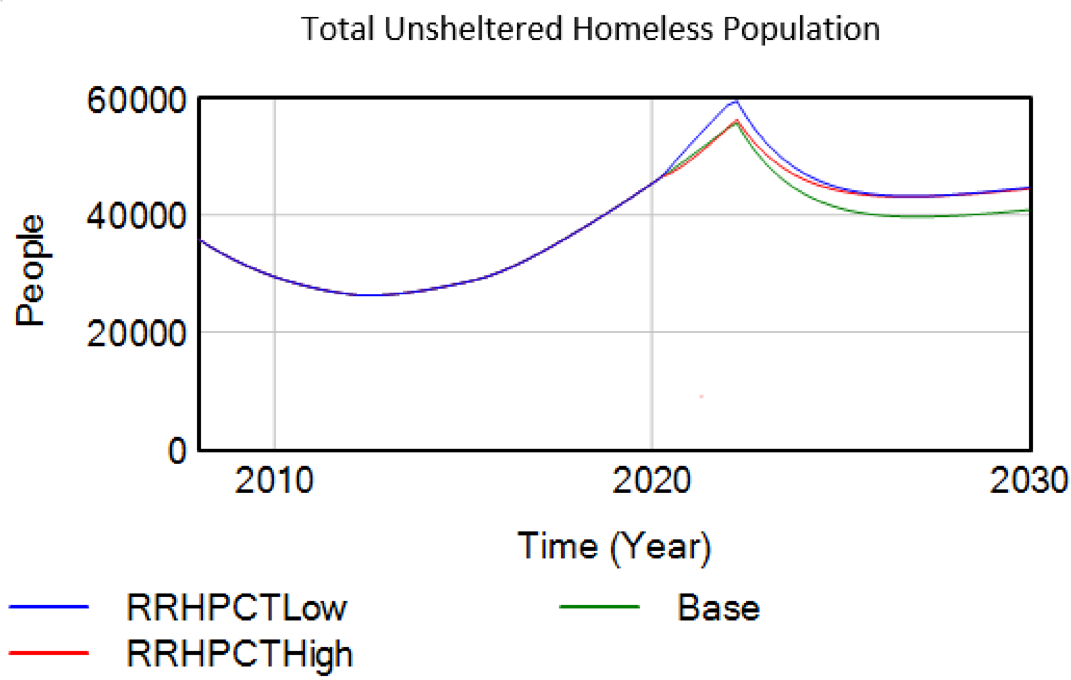


Figure 4-3-3-1. RRH Capacity Comparison

The simulation results indicate that regardless how large or small proportion unsheltered homeless RRH can take, it seems that the RRH program does not have a positive effect on solving unsheltered homelessness. More quantitively, either a higher or lower inventory in RRH bed would lead to an average of 5,000 homeless increases (the distance between the overlapped red/blue line and the green line). Figure 4-3-3-1 shows that the lower RRH bed inventory results in simultaneous increase in homeless population. The higher RRH bed inventory results in a lagged increase in homeless population. The benchmark model (the green solid line) generates a better outcome than the other two situations. Note that the higher fractional RRH inflow rate (red line) may lead to a slightly better outcome after 2020, 100 fewer unsheltered homeless people. But its side effect of the increase in homeless return becomes significance as soon as the homeless exit the program. As an increase of 3,000 more returning homeless emerges in the following year. On the other hand, lower the RRH intake ratio may lead to a peak in the unsheltered homeless population, roughly 4,000 increases in the unsheltered homeless population in the first year. But it generates 2,000 fewer returning homeless.

To see the difference effect that RRH may have on non-chronical homelessness, Figure 4-3-3-2 depict the simulated outcome when there is not any RRH supply. Figure 4-3-3-3 shows the simulated outcome if the RRH supply is 10 times current supply.

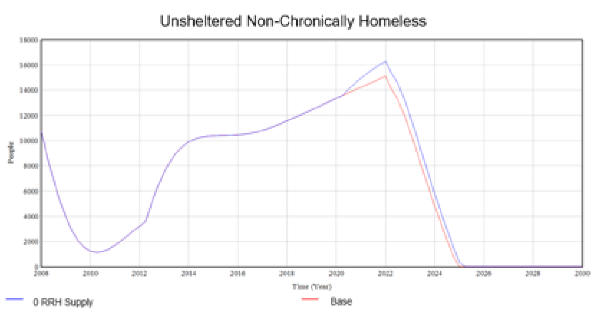


Figure 4-3-3-2.

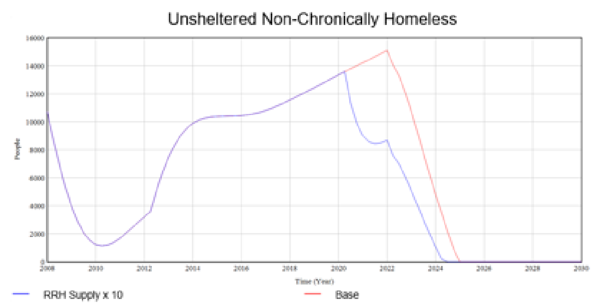


Figure 4-3-3-3.

The simulated outcomes indicate that even though RRH eases the unsheltered non-chronical homelessness, the RRH approach is not effective approach for LA to combat the unsheltered chronical homelessness.

4.3.3.2 The Length of Stay in Rapid Re-housing

The length of stay in the RRH program is evaluated by reducing the length of the program from 0.5 year or 6 months down to 0.2 year or 2.4 months, then extending it up to one year. The result is shown in Figure 4-3-3-2-1.

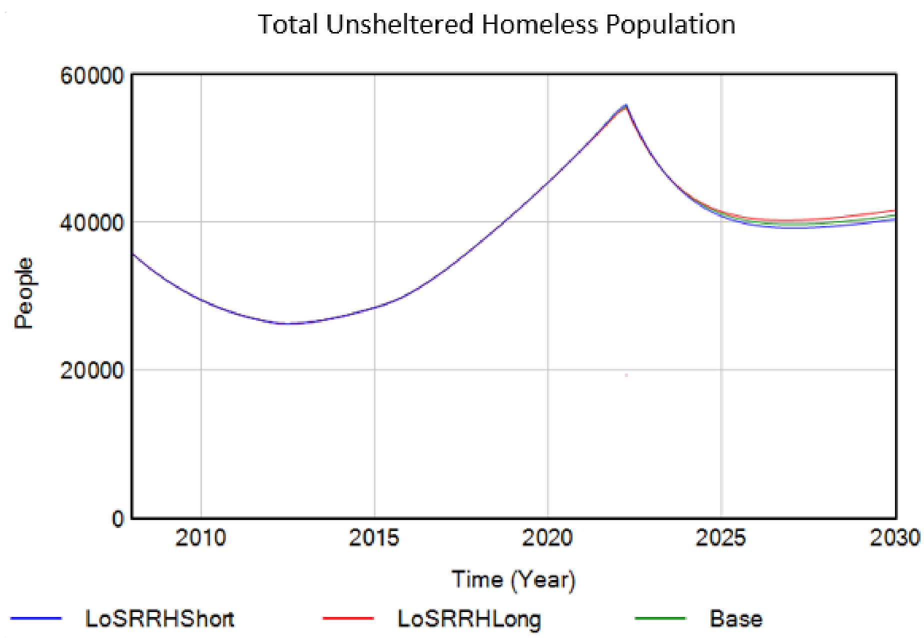


Figure 4-3-3-2-1. The changes in the length of stay in RRH result in a small effect on overall homelessness

The simulated result suggests that the length of stay in the RRH has an insignificant effect on overall unsheltered homeless mitigation. 1.5-month RRH program (the blue line) leads to a 30 people decrease in the unsheltered homeless population, while a 12-month RRH program (the red line) leads to 60 more unsheltered homeless. It once again indicates that the RRH is not a good approach for mitigating LA homelessness.

In this section, the RRH program is evaluated from the perspective of its capacity and the length of the program. Keep in mind that those who stay in the program are not counted as homeless and roughly 11 percent homeless use RRH. The length of the program has limited impact on the overall homelessness. In the next section, the impact of transitional housing on the chronically homeless people is evaluated.

4.3.4 Scenario IV Transitional Housing - Transition Rate

To see if the impact of the transition from the TH program into the RRH program has an impact on the unsheltered homelessness, the transition ratio from TH to RRH is increased from 0.02 to 0.3 then increased to 0.9. The test aims to evaluate how directly transferring 30 percent and 90 percent homeless people who exit the transitional housing to the rapid rehousing affects homelessness. The simulation result is shown in Figure 4-3-4-1.

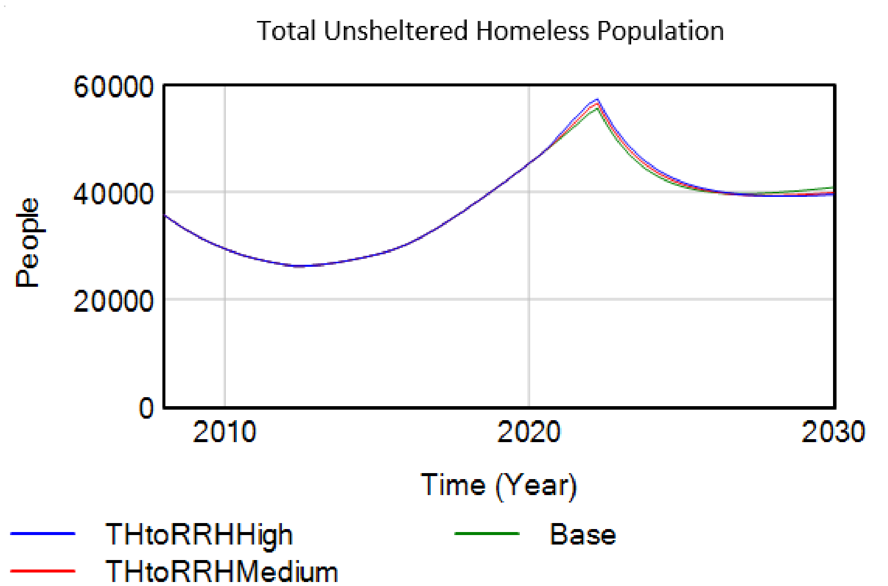


Figure 4-3-4-1. The Simulation Result Based on the Changes of the Transition Ratio Between the TH and the RRH Program

The changes in the transition rate from TH to RRH do not affect overall unsheltered homelessness too much. The transition from TH to RRH has a small positive affect on unsheltered homelessness. One reason could be that the average TH supply is around 5,000, and the average RRH bed inventory is around 7,000. Compared to more than 45,000 unsheltered homeless, the impact of both TH and RRH on the total unsheltered homelessness is insignificant.

So far, we have examined the effect of the short-term housing on the unsheltered homeless population. The simulation results indicate that the short-term housing is neither effective nor efficient on combatting homelessness. So, before moving forward to an optimal assumption, the impact of the permanent supportive housing is assessed in the following section.

4.3.5 Scenario V Permanent Supportive Housing

The permanent supportive housing as a focus of the Housing First policy has been implemented since the 1980s. The PSH aims to provide individuals and families experiencing long-term homelessness with supportive housing by funding high quality tenant services and, when needed, local rental subsidies (County of LA). The PSH takes care of disabled people who usually are chronically homeless. The demand for PSH is far greater than the supply. It results in many homeless who cannot be settled in the PSH sleeping on the streets.

It seems manifest that California has the most unsheltered homeless population in America in the past few years. Is it possible that people experiencing homelessness in LA are not interested in shelter or permanent housing? I have interviewed some homeless in the City of Riverside and I found that the homeless people regardless of their ages and gender, desired to live in their own place. The most common reason, which prevents them from being stabilized by a government housing program, is that the unsheltered homeless' Coordinated Entry System (CES)[21] scores do not reach the minimum requirement for them to be qualified for the permanent supportive housing. Most of the homeless people I met have been homeless for many years without taking government housing assistance. One 23-year-old young adult told me that he started wandering

[21] https://www.lahsa.org/ces/

between jail and the street when he was 16 years old. Other young adults wished for a single residency unit. Most of the unsheltered homeless people in Riverside would choose first to live at a single residency unit as their primary residence, with sleeping on the streets as their second choice. It implies that a shared-bedroom shelter might not be appealing to the young unsheltered street dwellers.

4.3.5.1 Chronically Homeless Directly Use Permanent Supportive Housing

If the chronically homeless can be smoothly settled into PSH in a timely manner, how does this affect the unsheltered returning chronically homeless population? Let the fractional rate of the unsheltered chronically homeless to use PSH be decreased from 20 percent to 10 percent, then increased to 30 percent, leaving all other conditions unchanged. Figure 4-3-5-1 illustrates the simulated outcomes.

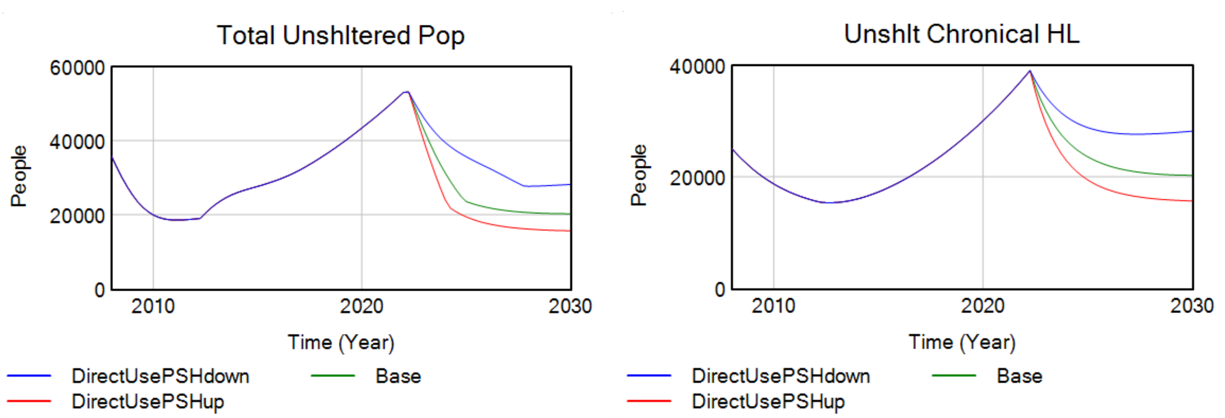


Figure 4-3-4-1(left and right). Simulated Result Comparison Between Increased and Decreased Fractional Inflow Rate for the Chronically Homeless to Directly Apply for PSH

The results suggest that this approach has a significant impact on chronical homelessness. On average, a 10 percent increase in directly usage of PSH ratio leads to 3,954 decreases in chronically homeless population, which is represented by the area between the green base line and the red line on the right in Figure 4-3-4-1.

In the benchmark model, the SD model is constrained by two conditions for the parameter initialization. The percentage of chronically homeless who directly use PSH is dependent on the size of the chronically homeless who use other housing or services facilitates. The simulation under this scenario indicates that if the chronically homeless can be taken from the street into PSH or be provided needed services and then move into the PSH, the cascade effect of the PSH combined with necessary services together produce a positive impact on reducing overall homelessness burden.

In Chapter 2, Table 2.5.1 shows the cost comparison between the PSH and the RRH per unit per person in 2017. As of 2020, there were about 46,000 homeless people. Around 23,000 homeless people used short-term housing including the emergency shelters, the TH, the RRH, and about 22,000 homeless people used the PSH program. If all the unsheltered homeless were served in PSH, the cost in 2021 would be 263 [22] million dollars. The cost for the short-term housing was 127 [23]million dollars. Therefore, the estimated cost for using the PSH alone in 2021 would be 272 [24] million dollars.

Table 4-3-5-1 and Table 4-3-5-2 show comparison results between costs and outcomes by using the PSH program and other short-term programs based on current funding allocation strategy in the base year of 2020 and the predicted homeless population in 2021.

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[22] 46,000 people × $5,884[22] per unit ×1.08 including 8% inflation rate
[23] 22,000 people x $5,345 per unit x1.08 including 8% inflation rate
[24] 262 million – 127 million + 24,000 existing people in the PSH x $5,884 x 1.08 including 8% inflation rate

Table 4-3-5-1 The Cost and Outcome Comparison by Supportive Programs in 2021

Base Year: 2020	PSH	ES+TH+RRH+SSO
	Base	Base
Funding	$125,259,861	$129,819,443
Cost Per Person	$5,884	$5,345
Homeless Return	4%	10%
Expected to be Served Pop	21,288	24,286
Expect Returned Homeless	851	2,429
Total Unsheltered Pop Next Year	46,090	

Table 4-3-5-2 The Cost and Outcome Comparison based on Current Funding Allocation Strategy

2021 Funds Allocation Strategy	PSH	ES+TH+RRH+SSO
	1.05 x	1.14 x
Funding	$146,253,414	$147,994,165
Cost Per Person	$5,884	$5,346
Homeless Return	4%	10%
Expected to be Served Pop	24,856	27,686
Total Unsheltered Pop Next Year	42,402 [25] + New Homeless Input	

Table 4-3-5-2 suggests that without any new homeless input, under the current policy, 1.05 times increase in the PSH program and 1.14 times in all other programs, the total unsheltered homeless in 2021 would be 42,402, less than 4,000 unsheltered homeless population decrease. It indicates that the current funding allocation approach has a limited effect on mitigating the unsheltered homelessness.

[25] 42,402 = 46,090 – (24,856-21,288) – (27,686 – 24,286) + 947 + 2,429

What if all the homeless are served in the PSH? Table 4-3-5-3 lists the costs and outcomes when there was sufficient fundings to support all the homeless in the PSH by 2030.

Table 4-3-5-3 The Annual Cost and Outcome When PSH alone Confronts Homelessness

PSH Only	PSH
Fund needed	597 million ~ 884 million
Cost Per Person	5,884 ~ 8,708
Homeless Return	0.04
Total served pop	101,500[26]
Expect Returned Homeless	3,962
Total Unsheltered Pop Next Year	3,962 + New Homeless Input

Table 4-3-5-3 suggests that if there was 2.26 to 2.89 times the total funds spent on PSH every year, by the end of 2030, the PSH inventory would be sufficient to serve all the homeless including renewing the existing grantees and new grantees.

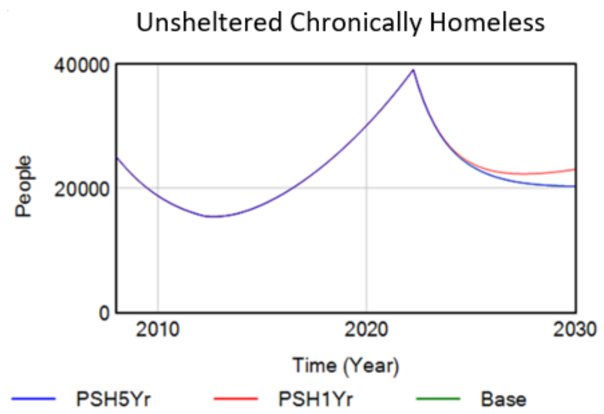
4.3.5.2 Length of Stay in Permanent Supportive Housing

It is also important to understand how long the PSH program needs to be so that it can be effective and efficient for mitigating homelessness. The PSH is essential for the chronically homeless to have sustainable housing and health services. To examine whether the length of the program has an impact on homelessness, the length of the PSH is decreased from the initial 20 years down to 5 years, then to 1 years, respectively, holding other factors constant. Figure 4-3-5-

[26] Grants in 2020 was $125,259,861+$129,819,443 or $255,079,304

101,500 is the simulated PSH population in 2030 based on the SD sensitivity analysis.

2-1 depicts the simulations on unsheltered chronical homelessness. Figure 4-3-5-2 portrays the simulations on non-chronical homelessness.



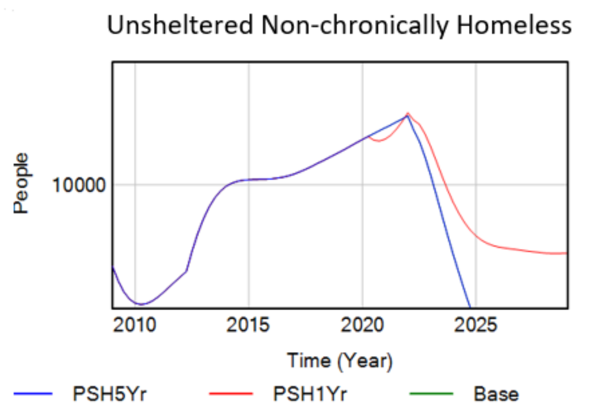


Figure 4-3-5-2-1. **Figure 4-3-5-2.**

The simulated outcomes suggest that the length of PSH primly effects on non-chronically homelessness than chronically homelessness. A one-year PSH program results in an average around 6,000 unsheltered non-chronically homeless people increase. A five-year PSH program is not different from a 20-year PSH program. The length of the housing program is critical as it affects the costs of the long-term supportive housing. If a five-year housing and service support are sufficient for the non-chronically homeless, there is no need to continue providing PSH services for those non-chronically homeless who have been in the PSH program for 5 years.

4.3.6 Beyond Housing – Multivariate Simulation

What if LA, rather than providing long-term housing, such as PSH with services included, focuses on only utilizing health services and social supportive services? To examine the impact of services on homelessness, the fractional rate of utilization for the mental services and social services increases from 0.25 to 0.5. The test aims to find out how the expansion of the health services and social support to a half of the homeless population affects homelessness. The simulation results are shown in Figure 4-3-6.

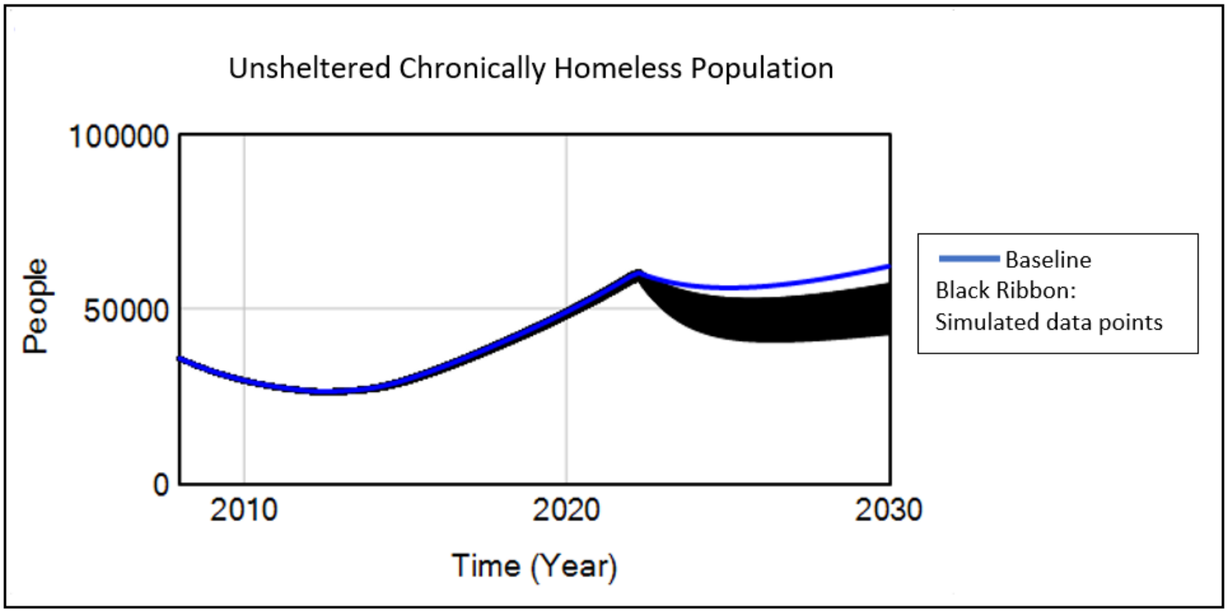


Figure 4-3-6. The Multivariate Simulation of the Increased Social Services and Mental Health

The initial value for mental health services fractional rate is 0.2, in the scenario test, this ratio is randomly drawn from a uniform distribution between 0.25 and 0.5. The result indicates that the services alone could mitigate unsheltered chronically homelessness. Note that this approach only impact on the chronically homeless mitigation since the non-chronically homeless do not need mental health services.

4.4 Equilibrium Analysis Based on Optimal Conditions

By far, the efforts of RRH, TH, and PSH have been evaluated when holding other variables constant. It is observed that the housing subsidization for the high risk homeless, the eviction ratio over the total chronically homeless population, and the directly usage of the PSH program for the unsheltered homeless tend to have greater impact on homelessness than other factors. The next attempt is to use the multivariate sensitivity analysis technique to find out the simulated outcomes between 2021 and 2030 under a set of optimal conditions that are not evaluated by the scenario analysis.

Prior simulations could not generate zero unsheltered homelessness. The last attempt is to run a sensitively analysis based on increasing fractional inflow rates of chronically homeless mental services, social services, the direct PSH assistance between 0.5 and 1, meanwhile, controlling the RSO housing fraction rate between 0.9 and 0.95, and eviction fractional rate between 0 and 0.01, and holding other variables unchanged. The primary phase plots are introduced first before reviewing the system's macro level behaviors.

Phase portraits are a useful tool in studying equilibrium status in a dynamic system. It helps evaluate the geometry of system behavior using plots of typical trajectories in the state space. Behavioral geometries identify equilibria, including stable and unstable fixed points, attractors, repellors, saddle points and other higher order behaviors. In a phase portrait plot, x-axis and y-axis represent two different phases of interest.

Figure 4-4-1 is a phase portrait plot that depicts the relationship between the chronically homeless growth rate and the total unsheltered homeless population. In this plot, the trajectory is labeled by each time step. Note that when the chronically homeless inflow increases between 2008 and 2012, the total unsheltered homeless population decreases, but increases between 2012 throughout 2022. Under the optimal assumption mentioned above, most chronically unsheltered homeless could be moved off the street quickly, from over 55,000 to 20,000 in three years. However, 20,000 unsheltered homeless is an equilibrium in the system. In other words, the difference between all inputs (or new homeless and returning homeless) and all outputs (those who use short-term and long-term housing) are balanced. The unsheltered homeless population neither growing nor reducing after the system reaches this point.

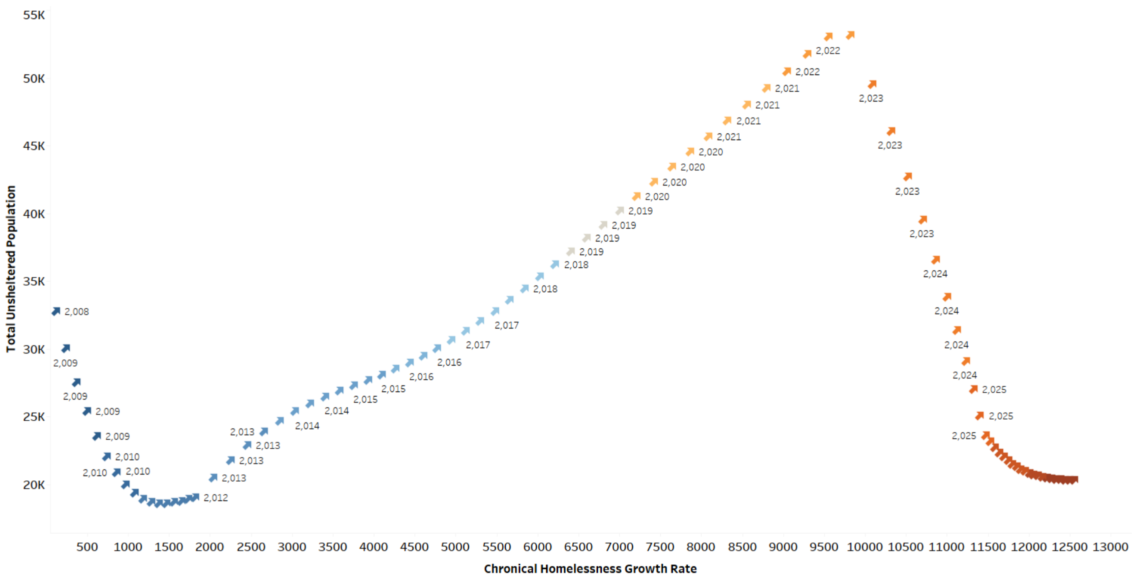


Figure 4-4-1. A Phase Portrait between the Chronically Homeless Growth Rate and the Total Unsheltered Homeless

Figure 4-4-2 portrays the relationship between the outflow rate for the non-chronically homeless who exit shelter and the inflow rate for all the homeless who settle in the PSH program. Adding two more dimensions, time and the overall unsheltered homeless population, the plot shows that between 2008 and 2022, the shelter's exiting rate for the non-chronically homeless is much greater than the PSH's entering rate. It leads to the unsheltered homeless population continuously growing (larger dot presents a larger homeless population). Even the PSH entering rate increases after 2020, the unsheltered homeless population does not show a significant decrease until 2022.

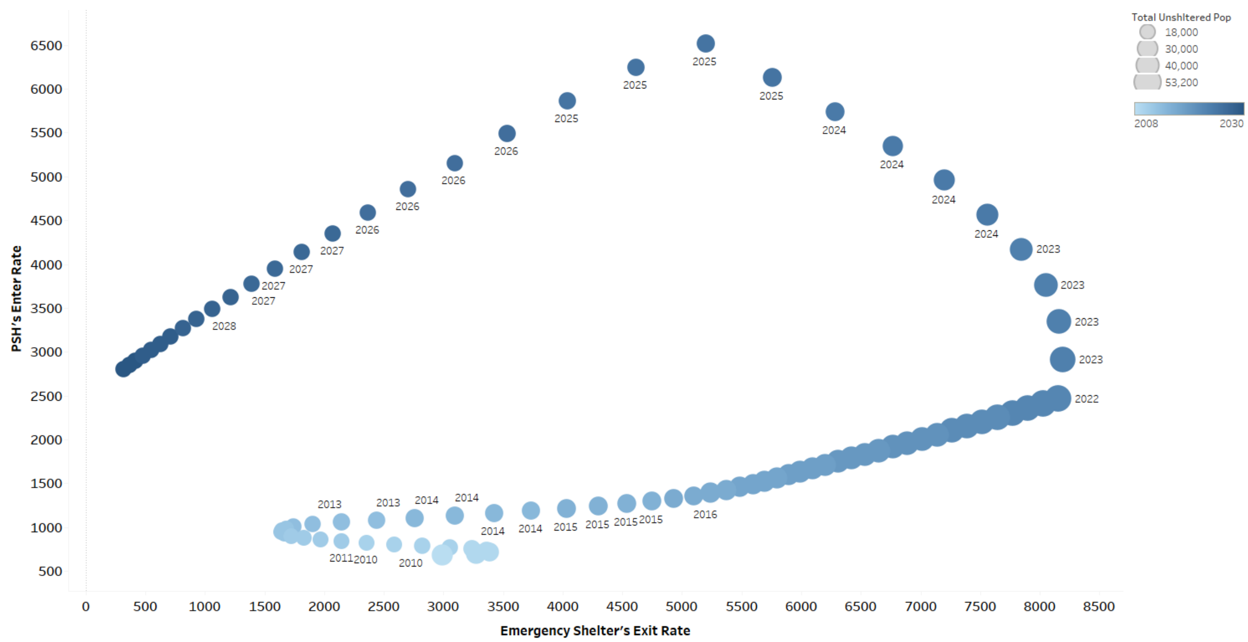


Figure 4-4-2. A Phase Portrait Depicts the Relationship among ES, PSH, and Total Unsheltered Homeless Over Time

Note that in Figure 4-4-2, from 2008 to 2014 (bottom) the rate of exiting shelter is low. From 2016 to 2022 the rate of exiting shelter still increases slowly. Under the optimal strategy, the magnitude of the PSH usage rate between 2022 and 2025 is increased. The outcome after implementing this strategy is that after 2025 the rate of the PSH usage starts sliding down when the homeless population declines. Figure 4-4-2 also identifies an equilibrium that is when the homeless exiting shelter rate around 4,500 people per year and the homeless entering PSH rate around 3,500 people per year. The unsheltered homeless population status remains stable.

The next phase portrait, Figure 4-4-3, aims to explore the dynamic interaction between the chronically homeless population (x-axis) and the non-chronically homeless population (y-axis).

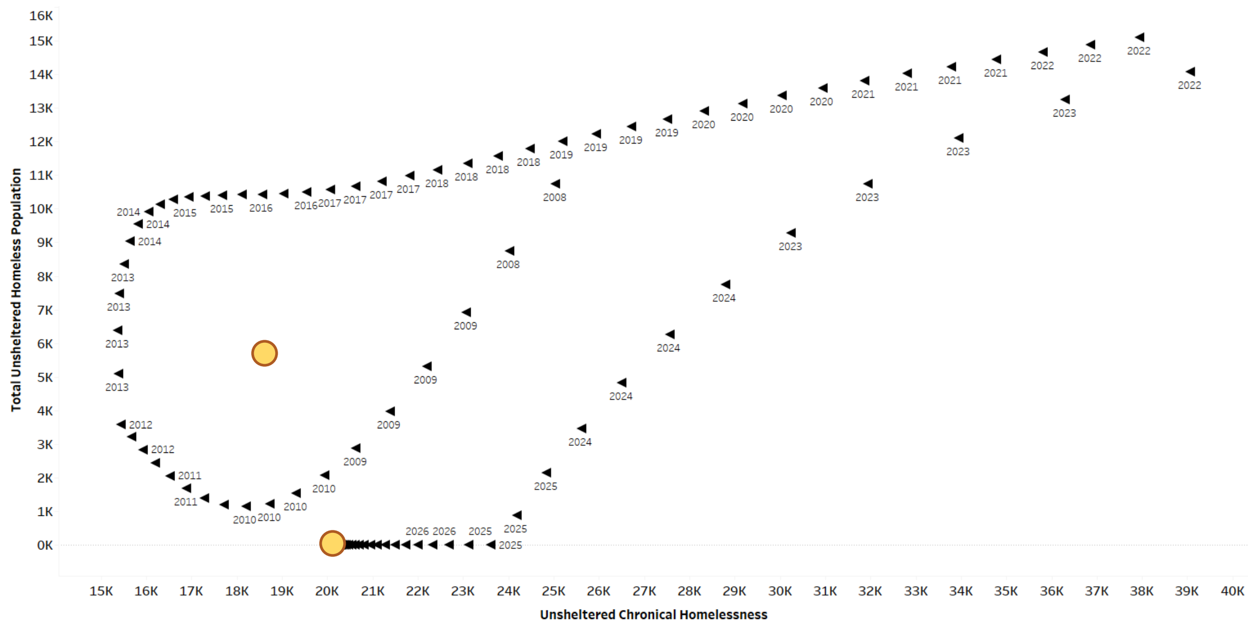


Figure 4-4-3. A Phase Portrait Between the Chronically Homeless and Non-Chronically Homeless population

Figure 4-4-3 depicts a circle pattern between the unsheltered chronically homeless (x-axis) and the non-chronically homeless (y-axis). Both the chronically homeless and the non-chronically homeless quickly decrease between 2008 and 2012. Then, suddenly, between 2012 and 2015, the non-chronically homeless population peaks while the chronically homeless population stays low. Then the chronically homeless population grows faster until 2022. This exponential increase in unsheltered population is led by the increase in returning homeless from short-term housing programs.

Note that towards the end of the simulation, under the optimal solution, even though there will not be any non-chronically homeless, around 20,000 unsheltered chronically homeless remain. Two equilibriums are detected in Figure 4-4-3. One equilibrium is located in the center of the circle between 2008 and 2018. It represents the chronically homeless, around 19,000, and the non-chronically homeless, around 6,000. This status quo was broken after 2018 and the system became far from equilibrium between 2018 and 2020. Without an optimal strategy, the system would most likely continue moving away from the prior equilibrium. But under the optimal strategy, an ideal equilibrium emerges and lands on the x-axis which means zero non-chronically homeless with 20,000 chronically homeless.

A phase plot, Figure 4-4-4, shows a pairwise relationship between the net rate of change in the non-chronically homeless population and the total non-chronically homeless population.

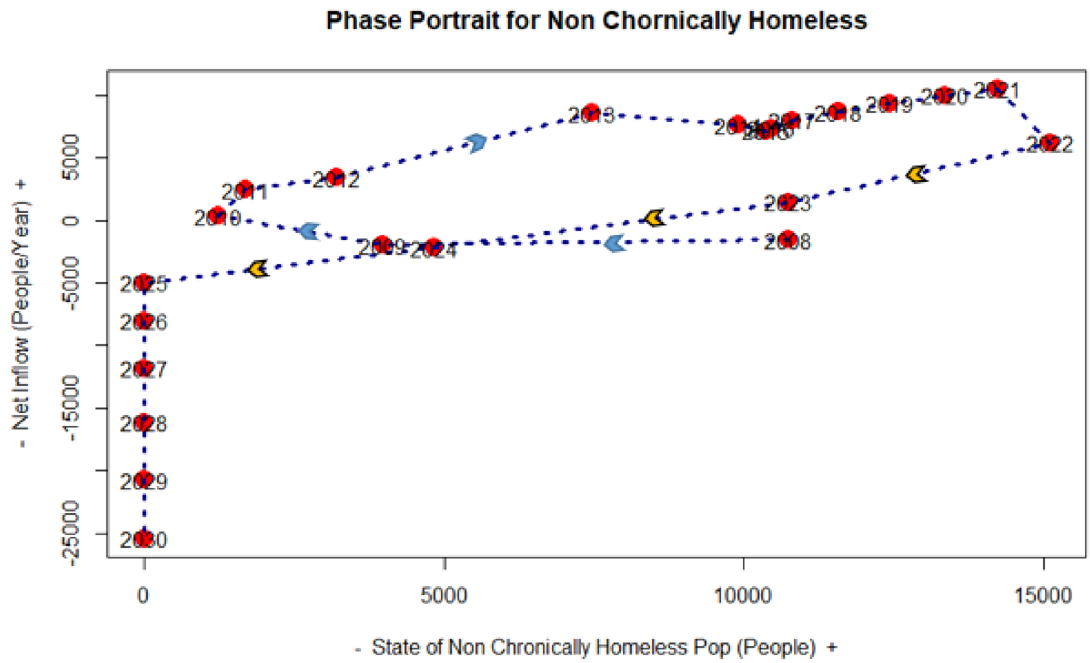


Figure 4-4-4. A Phase Plot of Stock and Net Inflow for the Non-Chronically Homeless Based on the Higher Order Derivative

Note that the equilibrium starts in year 2008 (initial year), the non-chronically homeless population is stable around an average of 7,500 increases between 2008 and 2020. After 2020 under the optimal strategy, the non-chronically homeless growth rate decreases over time, which results in a direct reduction in non-chronically homeless population. Between 2025 and 2030, the negative growth rate in the non-chronically homeless would not make any difference on the total non-chronically homeless population as all the non-chronically homeless are removed from the streets by 2025. Figure 4-5-4 depicts the cause of the macro behavior change in the unsheltered non-chronically homeless population.

Compared with the non-chronically homeless population, a phase portrait for the chronically homeless is plotted and shown in Figure 4-4-5.

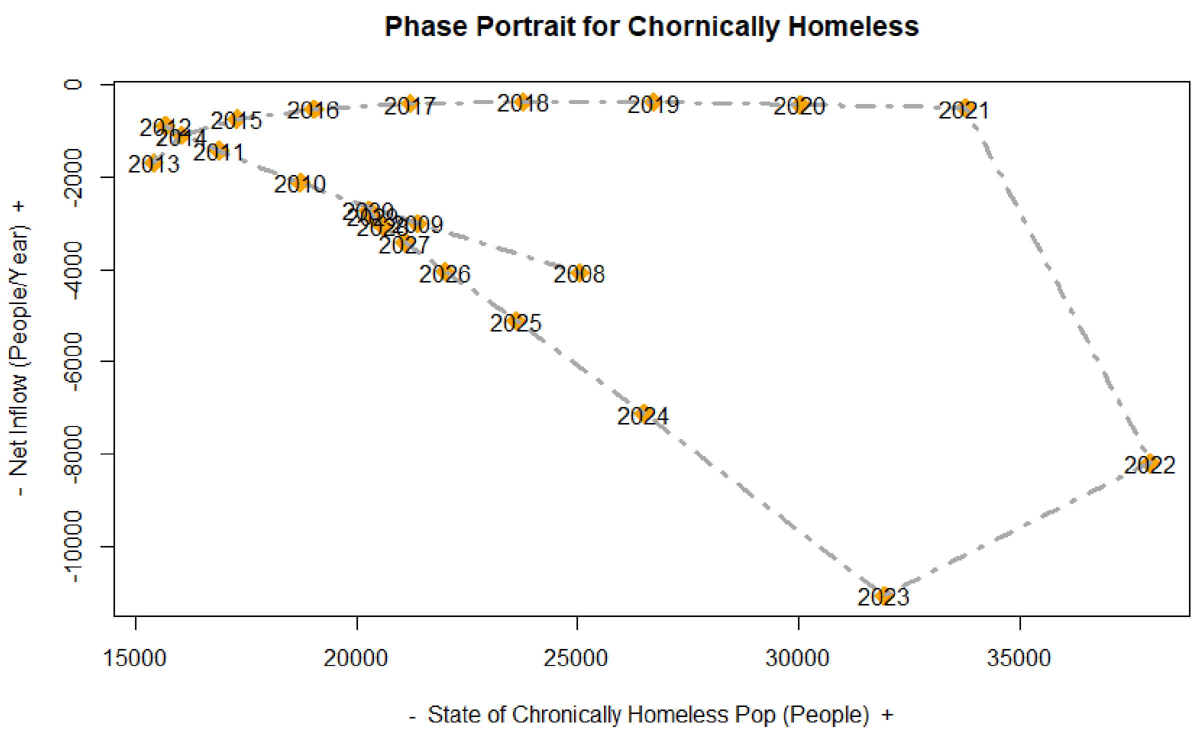


Figure 4-4-5. A Phase Plot of Stock and Its Net Inflow for the Chronically Homeless Based on the Higher Order Derivative

Note that the state of chronically homeless population is a relatively stable cycle between the starting point 2008 and the ending point 2030. Between 2027 and 2030, the number of the unsheltered chronically homeless stays around 20,000.

4.5 System Behavior under Optimal Assumptions:

A Combination of Optimizing All Key Factors

Under the optimal assumption, the system behaviors for the total unsheltered homeless population, the total unsheltered chronically homeless, and the total unsheltered non-chronically homeless are displayed in Figure 4-5-1, Figure 4-5-2, and Figure 4-5-3, respectively.

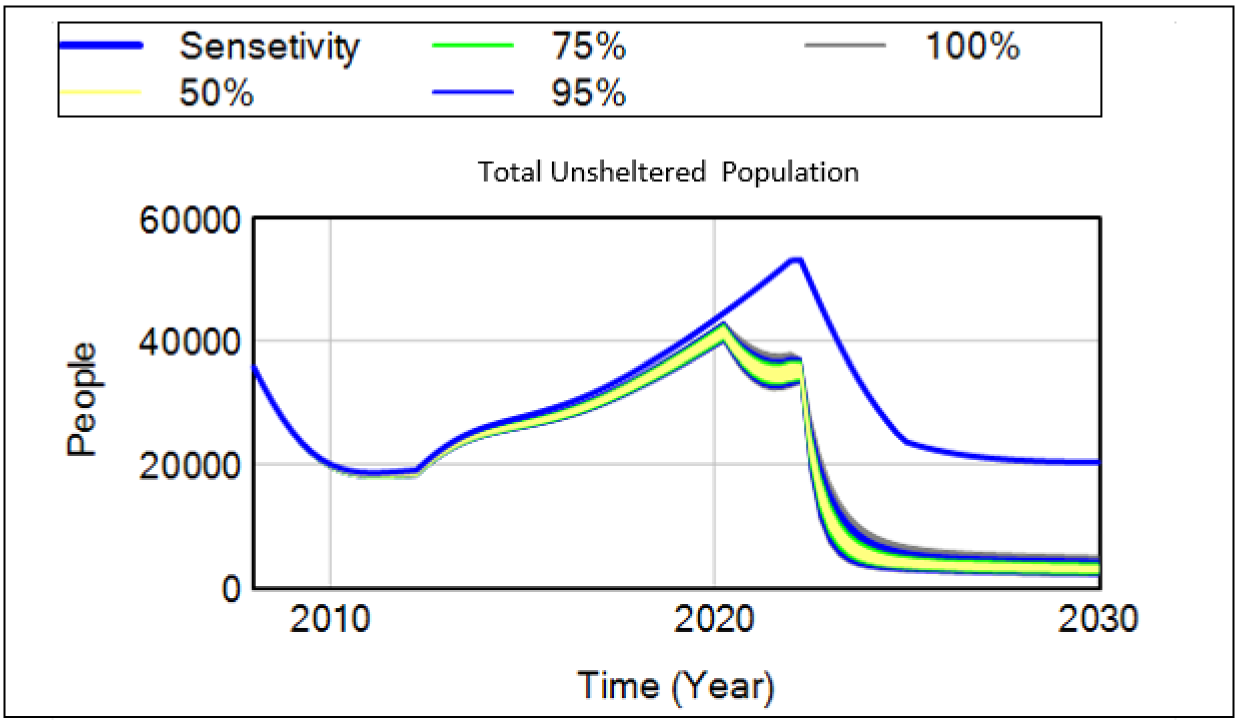


Figure 4-5-1. The Total Simulated Unsheltered Homeless Population through an Optimal Solution

It seems that the total unsheltered homelessness is approaching zero after 2022.

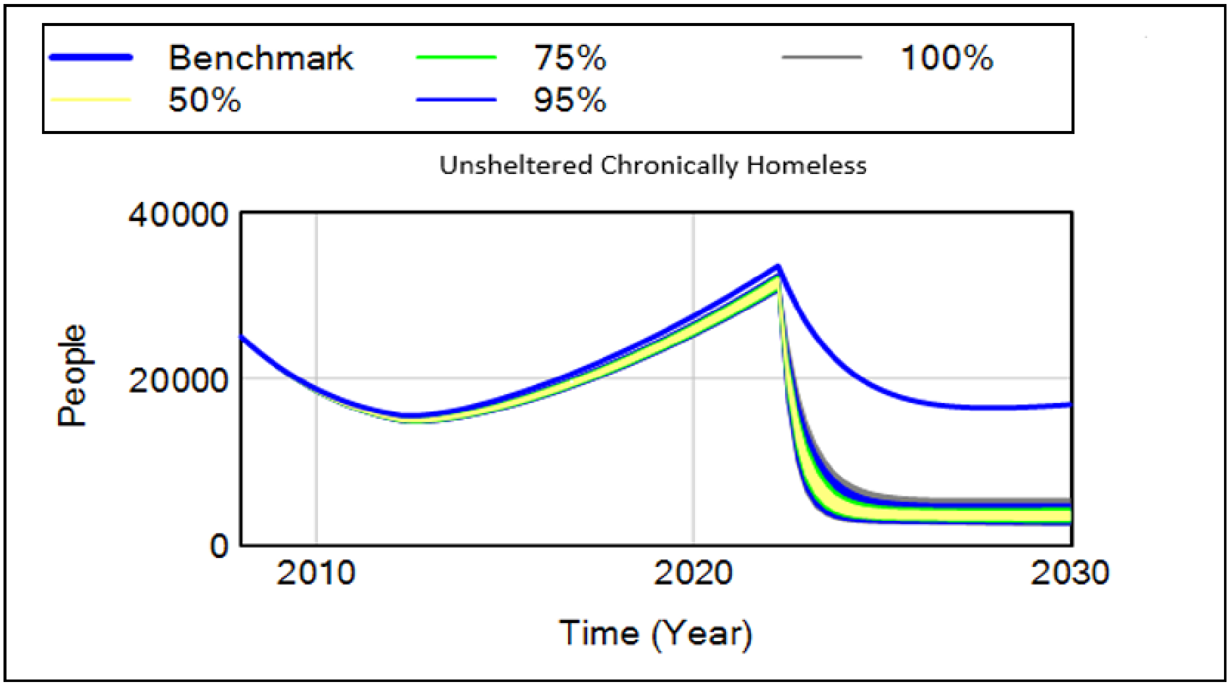


Figure 4-5-2. The Total Unsheltered Chronically Homeless Simulated through an Optimal Solution

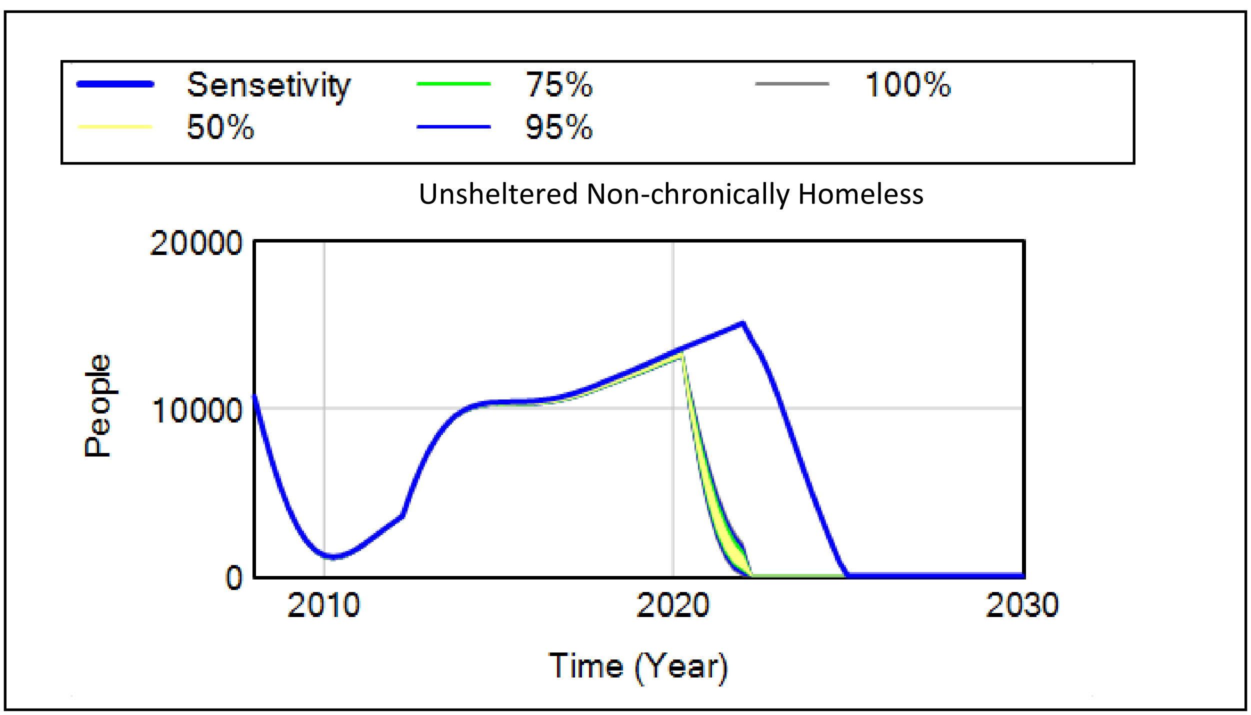


Figure 4-5-3. The Total Unsheltered Non-Chronically Homeless under the Optimal Solution

The simulation results suggest that under the most ideal conditions, all the non-chronically homeless can be fully stabilized. The number of chronically homeless residuals remain 300.

4.6 Monte Carlo Simulation – Robustness Analysis

Lastly, to be more confident about the estimation of Los Angeles homelessness by 2030, Monte Carlo simulation based on the optimal strategy is conducted. The input parameter setup is shown in Table 4-6-1. The model generates 200 experiments. The simulation results are displayed in Figure 4-6-2.

Monte Carlo Sensitivity Simulation Setup

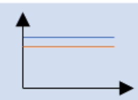
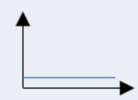
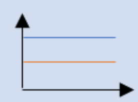
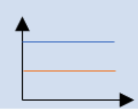
Parameter	Min	Max	Distribution
RSO ratio	0.8	0.95	
Eviction ratio	0	0.01	
Directly use PSH ratio	0.5	1	
Health serv. support ratio	0.5	1	
Chronical HL social service ratio	0.5	1	

Figure 4-6-1. Monte Carlo Robustness Simulation Setup. The key variables used for controlling homelessness are RSO ratio, eviction ration, directly using PSH ratio, PSH's health services and social services ratios.

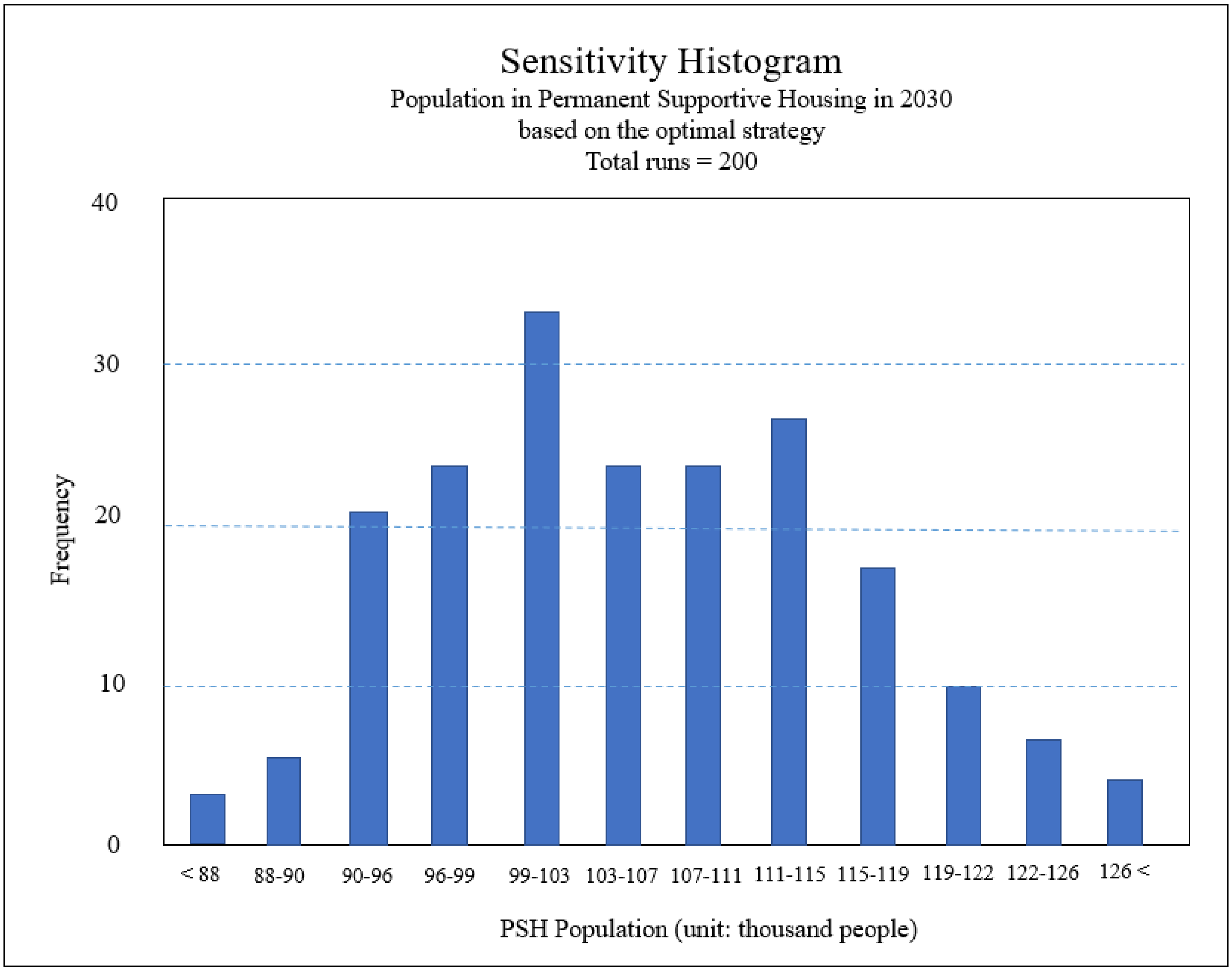


Figure 4-6-2. Sensitivity Histogram of the Simulated Population in PSH in 2030 When the Optimal Strategy for Homelessness is Applied

Figure 4-6-2 suggests that in 2030, under the optimal strategy, at the 90 percent confident level, the PSH population in 2030 would be between 90,00 and 122,000. Using the most frequent population interval, 99,000 and 103,000, the average population in 2030 would be 101,500. In 2022, the reported Los Angeles homeless population was over 69,000, and PSH population was around 24,000. Within 10 years, the demands for PSH must be four times it was in 2022.

Chapter 5

Implementation and Recommendations

The chronically homeless population has risen significantly over the past five years and is anticipated to rise even more in the near future due to the response of the City and County of Los Angeles to the SARS-CoV-2 pandemic. Los Angeles must develop more robust, systemic, and sustainable responses to the needs of this population. With an inflow that exceeds the outflow, and 35 percent of those experiencing homelessness this year experiencing it for the second, third, or fourth time, it is clear that current efforts are falling far short (LAHSA, 2020a). A brief comparison of the costs and benefits of short-term and long-term support for homeless people is shown in Table 5-1.

Table 5-1 Costs and Benefits Comparison between Short-term and Long-term Supports

Based on 46,090 homeless in 2020	Temporary Supports	Long-term Supports	No Support
Estimated Costs per person per year	$5,345	$5,290	$70,000
Expected Outcomes: changes in total unsheltered homeless	-640	-45,503	0

Table 5-1 displays a snapshot of how two homelessness strategies affect homelessness in Los Angeles. The cumulative cost of PSH is huge (Table 1-5-2), but PSH also seems likely to prove distinctively effective. Table 5-2 summarizes expected outcomes of these strategies.

Table 5-2 Expected Outcomes based on Recommended Strategies

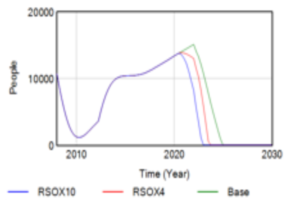
	Non-Chronically Homeless Pop	Chronically Homeless Pop
RSO Units ratio x 4 (0.05 to 0.2)	-14,00	X
Eviction ratio **down** by 0.005 (from 0.03 to 0.025)	-19,92	X
Direct Use PSH ratio **up** by 0.1 (from 0.2 to 0.3)	X	-3,954

Table 5-2 shows the predicted average annual reduced homeless population under the recommended policy during the simulation period of 2021 to 2030. The results from scenario analysis support the contention of Fowler et al. that keeping people in homes leads to a decrease in unsheltered homelessness. Also, the results showing that homelessness prevention and an increase in PSH reduce unsheltered homelessness align with the argument offered by Nourazari et al. Figure 5-1 compares the key policy levers and their effectiveness as well as associated annual costs.

A Panel Comparison Table for Three Key Policy Levers

1. Rent Stabilization Ordinance – Non-chronically homelessness

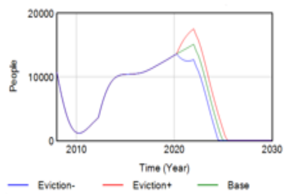
Average annual change in homeless population



RSO Ratio: up to 0.5 / 4 times:
1400 decreases in non-chronically homeless population

RSU Units	Est. Cost / yr.
+ 5,791,554	$521 million

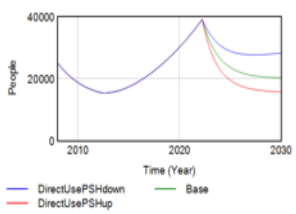
2. Eviction – Non-chronically homelessness



Eviction Ratio: down to 0. 25 / 0.83 time:
1992 decreases in non-chronically homeless population

Evicted Pop	Est. Cost / yr.
-11,000	$66 million

3. Directly use of Permanent supportive housing and services – Chronically homelessness



Direct PSH usage ratio: 0.3/ 1.5 times:
3954 decreases in chronically homeless population

PSH Units	Est. Cost / yr.
+ 101,500	$600 -$880 million

Figure 5-1. A Panel Comparison of Key Policy Levers and Their Associated Effectiveness and Costs

Based on evidence found in this study, recommended strategies of confronting homelessness are as follows:

- Avoid eviction and implement rent stabilization ordinance
    - Allocate $521 million as a housing subsidy to landlords or the non-chronically homeless people in order to prevent deeply-low-income renters from being evicted.
    - Ensure that grants are used properly for directly supporting the deeply low-income individuals and households but no other groups by requiring a third-party audit.
- Prioritize existing and new housing stock of PSH
    - Continue to prioritize PSH in policies designed to increase the housing stock by 80,000 or more by the end of 2030.
    - Consider ways, such as using vouchers and directly reimbursing landlords or the non-chronically homeless, to provide PSH that do not require the construction of new housing units, given the logistical, political, and bureaucratic challenges associated with building in Los Angeles.
- Housing is much more expensive because of multiple barriers of the kind of I have mentioned above. While housing cost is not the only problem confronting homeless people, eliminating the bureaucratic barriers to affordability seems likely to be hugely important to any genuinely systemic policy analysis.
    - Modify the eligibility barriers so that more homeless people are eligible for PSH, with the goal of ensuring that 101,000 PSH beds can be fully occupied by 2030 if needed.
- Increase the use of relevant services for chronically homeless people by increasing the service's ease and attractiveness.

- Work on chronically homeless people who are not willing to move off the streets
    - Knowing that the permanent supportive housing significantly reduces the costs for unsheltered homeless (on average, 6,000 per housed homeless per year vs 70,000 per unsheltered homeless per year). For chronically homeless people who are unwilling to move, it is vital for the city to let them be settled in homes by fostering long-term, trust-based relationships between homeless outreach workers and the chronically homeless people. Homeless outreach workers can be project managers. One goal for them is to convince the unwilling to move chronically homeless off the streets and live in homes.

Los Angeles should implement an integrated strategy which combines both the prevention and PSH approaches. For the prevention strategy, the policy maker should focus on preventing the most vulnerable people who are at the highest risk of being homeless from ending up on or returning to the streets. Previously homeless people discharged from incarceration or from mental health facilities can be prioritized. Combining a PSH approach with comprehensive health care services can be expected to prove effective.

Deeply low-income people—those who spend 42% of income on rent—can be supported by a rental stabilization policy. Los Angeles may prevent them from being homeless by controlling rental prices. Meanwhile Los Angeles can minimize the impact of the rent-controlled housing on housing stock and housing prices by implementation of the rent control ordinance in the selective areas.

Effective policy responses should acknowledge the needs of different subgroups of homeless people. Chronically homeless people, for instance, may not want to move out of neighborhoods where they feel they belong, and housing strategies serving them should typically seek to house them in these neighborhoods. People dealing with severe mental illness or substance abuse face additional obstacles to obtaining or maintaining PSH. These people need treatments and related services as much as or more than they need housing. But PSH is a good way for both types of homelessness. This study finds that it is sufficient to provide a less than 5-year PSH housing to the non-chronically homeless people.

Lack of social support can cause or exacerbate risks of homelessness. Most people who become homeless have live with relatives before losing access to housing (Liao, 2015). A program of offering subsidies to relatives and assistance to social workers in building ties with homeless people should be implemented on a broader basis.

Chapter 6

Conclusions and Recommendations for Future Studies

In Chapter 6, I summarize my conclusions regarding effective responses to the challenge of homelessness before identifying some of the study's limitations and noting ways in which my approach could be applied outside Los Angeles.

6.1 Effective Policies

The most effective approach to minimizing homelessness could be implementing an integrated approach consisting of a rent stabilization policy, an eviction protection policy, and a continuation of the existing Housing First approach with an emphasis on the PSH with associated long-term supportive services.

The SD model used in this study could be employed to help assess policies in cities and counties with characteristics similar to those of Los Angeles

Even though short-term housing approaches discussed in this study has less or no impact on homelessness mitigation, it is not as costly as long-term housing support. Consider short-term support for the homeless people as quick temporary assistance and ensure that the homeless can successfully transfer to the long-term supportive program if needed.

6.2 Limitations of the Study

I identify several limitations of this study. One limitation on the SD model's effectiveness is data availability. The integrated research approach has exhibited many attractive features. However, the study's results would be more useful if the empirical data related to relevant supportive housing, mental health spending, and services grants were accessible at census tract level. In this dissertation, I specifically studied Los Angeles homelessness; county- and city-level sample data for housing programs from HUD cannot be disaggregated into the census tract level in Los Angeles.

One limitation is the impact of the direct transition from emergency shelters to PSH is excluded from the scenario analysis. Policy makers in the places where face cold weather in Winter might be more interested in how sheltered homeless affects overall homelessness from a long-term perspective.

Another limitation is the impact of the pandemic on homelessness is not elaborated in detail. The reason is that from a system and long-term relationship perspective, a one-time event only creates a temporary fluctuation on the macrolevel behavior. The SD simulation suggests that it increases the magnitude of new homeless growth between 2020 and 2021 after the virus outbreak in 2019. But it has a trivial impact on homelessness from 2022 to 2030.

6.3 Applicability beyond Los Angeles

In order to use this model effectively in other cities, policy makers should, based on their cities' unique circumstances—including, but not limited to, their political environments, cultures, and financial capacities—consider adding or subtracting policy levels and adjusting parameter values accordingly. For instance, to predict the homeless population in New York, the number of sheltered homeless people would be increased and the number of those served by other short-term housing programs would be reduced. In yet other countries, it might be important to adjust parameter values in light of the amount of time people are able to remain in shelters or PSH.

Direct communication with homeless project managers and homeless people is worthwhile. It helps modelers, including me, to understand up-to-date bottleneck issues Furthermore, it would be interesting to use social network analysis to help determine how social ties and trust relationships between the unwilling homeless and the outreach workers seeking to assist them improve the well-being of the homeless people.

The use of permanent supportive housing combined with health and social services is the most effective means of confronting homelessness in Los Angeles. Unlike the use of rapid re-housing and other short-term housing approaches, this long-term approach has been shown to diminish the returning homeless population and reduce the annual costs on homelessness in response to chronically homeless population growth and in confrontations with limited fundings. Alternative approaches have not proven effective and have exhibited some tendency to increase returning homeless population. The combined PSH and services approach can be used to reduce the homeless population in other cities and counties and may thus serve to encourage the development of flourishing urban environments.

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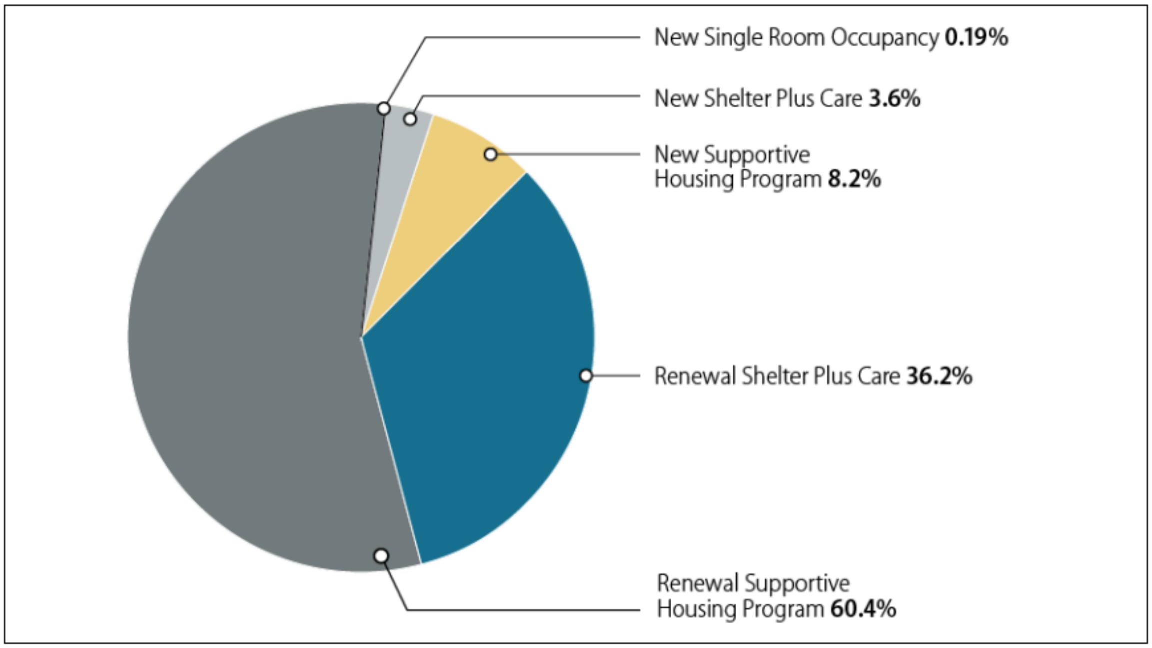
Appendix A - Homeless Assistance Grants Allocation in FY 2011

Figure A-1. FY2011 Percentage Allocation of Competitive Grants



Source: HUD FY2014 Congressional Budget Justifications, available at http://portal.hud.gov/hudportal/documents/huddoc?id=HOMELESSASSTGRANTS.pdf.

Appendix B - Los Angeles Homeless Model Initialization Setup

Level	Name	Unit	Equation/Value	Initial
1	Deeply Low Income People	People	high risk increase rate-prevention rate	410,260
2	Emergency Shelter	People	non chronic grow-exit shelter	5,000
3	Mental Health Served Pop	People	chronical to mental serv grow - grow	0
4	Perceived People Who Need PSH	People	change	0
5	PSH Demand	People	demand increase	0
6	Rapid Rehousing	People	STEP(TH return to RRH+TH to RRH+unshelt to RRH-exit RRH, 2012)	0
7	Transitional Housing	People	chronical to TH grow-exit TH-TH to RRH increase-TH to RRH increase	6,870

8	Unsheltered Chronically Homeless	People	IF THEN ELSE(Time<=2012, chron grow-chron decrease-chronical to TH grow, IF THEN ELSE(Time<=2022,chron grow-chron decrease -TH return to RRH rate,chron grow-chron decrease-TH return to RRH rate-chronical to mental serv grow-Chronic to PSH grow))	25,038
9	Unsheltered Non-Chronically Homeless Population	People	SINTEG(hl increase-hl decrease-non chronic grow-Street to RRH,10730,0,1e+06,:NA:,:NA:,:NA:)	10,730
Rate				
10	AVG DEEP LOW INCOME GROWTH RATIO	Dmnl/Year	RANDOM NORMAL(0.01, 0.1 , 0.07 , 0.01 , 1235)	NA
11	change	People/Year	IF THEN ELSE(Time<=2020 , difference/TIME NEEDED TO GET PSH, difference/TIME NEEDED TO GET PSH)	NA
12	Chronic (homelessness) decrease	People/Year	IF THEN ELSE(Time<=2020, Unshlt Chronical HL*HL DEATH RATE+Permanent Supportive Housing*0.05*CHROL STAB SER PCT , Unshlt Chronical HL*HL DEATH RATE+Permanent Supportive Housing*0.05*CHROL STAB SER PCT)	NA
13	chronic (homelessness) grow	People/Year	IF THEN ELSE(Time<=2012, PSH RETURN PCT*PSH Demand , PSH RETURN PCT*PSH Demand+RRH RETURN PCT*exit RRH*(1-"RRH RATIO FOR SELF-SUFFICIENCY")*0.1)	NA
14	chronical to mental serv grow	People/Year	IF THEN ELSE(Time>=2022,Unshlt Chronical HL*(MENTAL SER PCT-0), 0)	NA

15	chronical to TH grow	People/Year	IF THEN ELSE(Time<=2020, Unshlt Chronical HL*RATIO OF Chronic HL/W TIME for TH , Unshlt Chronical HL*RATIO OF Chronic HL/W TIME for TH)	NA
16	demand increase	People/Year	exit sheltere*0.5+exit TH	NA
17	Difference	People/Year	PSH Demand-Perceived People Who Need PSH	NA
18	emergency support ratio	People/Year	IF THEN ELSE(Time>2019:AND:Deeply Low Income People<=410260, PANDAMIC SUPPORT,0)	NA
20	enter PSH	People/Year	IF THEN ELSE(change>=Permanent Supportive Housing*PSH INCREASE RATIO, Permanent Supportive Housing *PSH INCREASE RATIO, change)	NA
21	exit PSH	People/Year	IF THEN ELSE(Time<=2020, (Permanent Supportive Housing/DURATION IN PSH)*PSH EXIT RATIO , (Permanent Supportive Housing/DURATION IN PSH)*PSH EXIT RATIO)	NA
22	exit RRH	People/Year	IF THEN ELSE(Time<=2012, 0, IF THEN ELSE (Time<=2020, Rapid Rehousing/DURATION IN RAPID REHOUSING*RRH RATIO FOR SELF SUFFICIENCY ,Rapid Rehousing/CHANGES IN RRH DURATION *RRH RATIO FOR SELF SUFFICIENCY))	NA
23	exit shelter	People/Year	Emergency Shelter/DURATION IN SHELTER	NA

24	exit TH	People/Year	Transitional Housing/DURATION IN TRANTIONAL HOUSING	NA
25	high risk increase rate	People/Year	pandemic shock+AVG DEEP LOW INCOME GROWTH RATIO*Deeply Low Income People	NA
26	hl decrease	People/Year	SelfSufficient Pop/1.5+DECREASE RATE*Total Pop Who Use A Housing Service/1.5+(chronical to mental serv grow+chronical decrease) /1.5	NA
27	hl increase	People/Year	IF THEN ELSE(Time<=2012, PSH Demand*(1-PSH RETURN PCT)/5 + Deeply Low Income People*EVICTION RATE, PSH Demand*(1-PSH RETURN PCT)/2 + Deeply Low Income People*EVICTION RATE+(1-RRH RATIO FOR SELF SUFFICIENCY)*0.1*exit RRH*(1-RRH RETURN PCT))	NA
28	non chronic grow	People/Year	IF THEN ELSE(Time < 2020, ("Unshlt Non-Chron Homeless Population"/W TIME FOR ES)*RATIO OF SHELTERED HL , ("Unshlt Non-Chron Homeless Population"/W TIME FOR ES)*0.6)	NA
29	prevention rate	People/Year	(emergency support ratio+prevention ratio)*Deeply Low Income People	NA
30	TH return to RRH rate	People/Year	IF THEN ELSE(Time<=2012, 0, Chronical HL*PCT CHROL TO RRH)	NA
31	TH to RRH increase	People/Year	IF THEN ELSE(Time<=2016, 0,IF THEN ELSE(Time<=2020, TH to RRH RATE*Transitional Housing, TH to RRH RATE*Transitional Housing))	NA

32	Total Pop Who Use A Housing Service	People	Emergency Shelter+Permanent Supportive Housing+Transitional Housing	NA
33	Total Unsheltered Pop	People	IF THEN ELSE(Unshlt Chronical HL+"Unshlt Non-Chron Homeless Population">=0, Unshlt Chronical HL+"Unshlt Non-Chron Homeless Population", 0)	NA
34	Street to RRH	People/Year	IF THEN ELSE(Time<=2012, 0, IF THEN ELSE(Time<=2020, "Unshlt Non-Chron Homeless Population"*FRACTIONAL RATE OF RRHed HL/W TIME FOR RRH, "Unshlt Non-Chron Homeless Population"*FRACTIONAL RATE OF RRHed HL/W TIME FOR RRH))	NA
35	AVG RSO Ratio	Dmnl/Year	IF THEN ELSE(Time<=2020, 0.05, RSO PCT)	
36	DURATION IN PSH	Year	IF THEN ELSE(Time<=2020, 20 , 20)	NA
37	DECREASE RATE	Dmnl/Year	IF THEN ELSE(Time<=2020, 1,SelfInd Ratio)	NA
38	DURATION IN PSH	Year	IF THEN ELSE(Time<=2020, 20 , 20)	NA
39	DECREASE RATE	Dmnl/Year	IF THEN ELSE(Time<=2020, 1,SelfInd Ratio)	NA

40	EVICTION RATE	Dmnl/Year	IF THEN ELSE(Time<=2020, 0.03, EVICTION RATIO)	NA
41	FRACTIONAL RATE OF USING RRH HL	Dmnl/Year	IF THEN ELSE(Time<=2020, 0.02 , RRH PCT)	NA
42	TH to RRH RATE	Dmnl/Year	IF THEN ELSE(Time<=2016, 0,IF THEN ELSE(Time<=2020, TH to RRH RATE*Transitional Housing, TH to RRH RATE*Transitional Housing))	NA
Constant				
43	RSO PCT	Dmnl/Year	0.05	NA
44	CHROL STAB SER PCT	Dmnl/Year	0.3	NA
45	DURATION IN ES	Year	2	NA
46	MENTAL SER PCT	Dmnl/Year	0.2	NA
47	NEW INPUT DUE TO COVID19	People/Year	1,000,000	NA
48	PANDAMIC SUPPORT	Dmnl/Year	0.5	NA
49	PSH EXIT RATIO	Dmnl	0.15	NA
50	PSH INCREASE RATIO	Dmnl/Year	0.1	NA
51	TH to RRH RATE	Dmnl/Year	0.02	NA
52	RATIO OF SHELTERED HL	Dmnl	0.3	NA
53	RATIO OF USING TH HL	Dmnl	0.25	NA
54	TIME NEEDED TO GET PSH	Year	0.25	NA
55	W TIME FOR ES	Year	0.5	NA
56	W TIME FOR RRH	Year	0.25	NA
57	W TIME for TH	Year	1.5	NA