Rental Assistance Amounts in Rapid Re-Housing

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12/2/2022

1. Abstract

In this paper I examine rental assistance amounts in L.A. County Rapid Re-Housing projects using log-linear regressions. I introduce the topic with a review of what Rapid Re-Housing is and what is generally unknown about it, I then detail the available data, and finally estimate and interpret models. The goal is to scrutinize the decision-making process behind subsidy amounts and examine how providers respond to participant needs. I find that out of observables, institutional factors such as what project a participant is assigned to carries much more weight in explaining assistance amounts than individual factors. I hypothesize that this is in large part driven by responses to county-level decisions on funding allocations, provider management philosophies, and local homeless population sizes.

2. Introduction

Homelessness in the United States is a pervasive problem. Numbers have declined nationwide, but keep growing in California and New York, driven by increases in their major urban centers. In their Annual Homeless Assessment Report, the U.S. Department of Housing and Urban Development, or HUD, reported 630,227 to 567,715 homeless persons in the US from 2009 to 2019, or an average 1% decrease every year (Henry et al., 2020). During this same period, counts for Greater Los Angeles in 2019 were 58,936, up approximately 10,000 persons from 2009 (48,053) (LAHSA 2010), (LAHSA 2020). Flaming & Burns (2017) attest that even these numbers are likely an under-estimation, based on LA's methods of counting.

A promising program is known as Rapid Re-Housing, where persons experiencing homelessness are assisted with finding private housing, usually apartments, and then their rent is temporarily subsidized. It is not well understood how subsidy amounts are chosen, and local providers are given broad flexibility in choosing subsidy amounts and longevity for each participant. This may be a source of its relative success, but also a source of uncertainty for participants weighing their options and researchers seeking to scrutinize the methodology (Gubits et al., 2013). Some providers use a formula taking into account a participant's income and expenses, others provide amounts that taper down over time (Ex. 100% of rent the first month, 75% the second month, etc.) They may also have a very flexible package, re-determined each month by a case worker's assessment of income and expenses (Gubits et al., 2018).

There are currently many studies on the effectiveness of Rapid Re-Housing as a treatment, both in Los Angeles County and elsewhere, but most treat it as a binary indicator, either the participant receives it or does not. To create an analogy with research on medicine, there is no research on the "dosage" of the treatment of Rapid Re-Housing (Gubits et al., 2018). We do not have a solid understanding of how rental assistance amounts are allocated, nor how the amount is to participant success (achieving financial independence).

While incorporating the amount of assistance may be important for evaluating Rapid Re-Housing, this does not exist in a vacuum. It is important to establish to what degree assistance for a given participant is determined by the participant's observable characteristics and circumstances, and how much potentially stems from local provider and case worker decisions. With this background in mind, this research seeks to gain insight on the variability of assistance amounts conditional on some observable factors, and what observable factors are most influential. In a well-functioning system, we expect subsidies to vary systematically with participant and market characteristics, Therefore, we expect to see providers responding to individual needs and circumstances, and this research may illuminate if this is generally the case or if other factors are more influential.

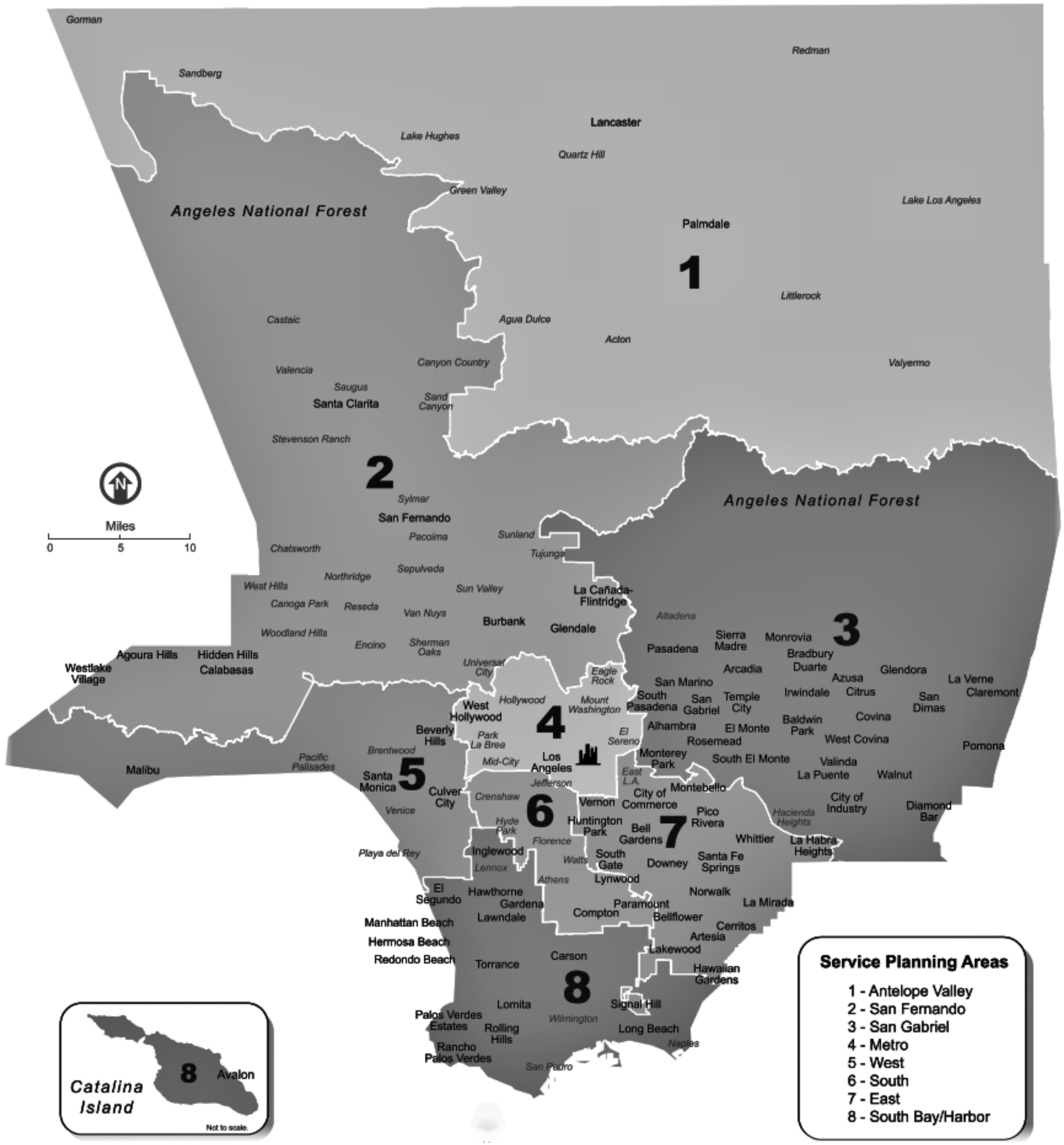
2.1 Rapid Re-Housing in Los Angeles

A provider, meaning a non-profit homeless services organization, is contracted by the Los Angeles Homeless Services Agency (LAHSA) to administer a Rapid Re-Housing project. These contracts are often renewed, and thus a single project can span multiple years. Examples of these organizations are People Assisting the Homeless (PATH) or Los Angeles Family Housing (LAFH). There are other types of projects, for example homeless shelters. For the purposes of this paper, project refers specifically to a rapid re-housing project.

Included in the contract for a project is a monetary grant, a quota of participants to serve, and performance benchmarks, such as 80% of participants exited to permanent housing in a given operating year. Portions of the grant may be earmarked for certain services, such as rental assistance for participants. A given project has two layers of managerial "quirks" and service philosophy that influences its decisions in how to serve participants, including how much per participant to spend. The first layer is the over-arching provider, which often manage multiple projects at any given time. The second is the individual case managers who interface directly with participants and may have some decision-making power how much financial assistance their assigned participants may receive.

The most important geography to homeless services in LA County is the Service Planning Area, or SPA. Figure A shows a simplified map of the area and how the 8 SPAs are delineated, retrieved from the website of the L.A. County Department of Public Health. Under the oversight of LAHSA, LA County uses a Coordinated Entry System (CES) to assign participants to different projects as space/funding is available. The intent is that participants will be referred to a project based on the SPA where they became homeless, and their population category. This category could be single adults, single youth (over 16), or families with children.

Figure A: Map of Los Angeles Service Planning Areas. (Source: LA County Public Health)



3. Data

This research uses a snippet of anonymized administrative data from the Homelessness Management Information System, as designed by the federal Office of Housing and Urban Development (HUD Exchange). The full dataset contains enrollments in Rapid Re-Housing programs as far back as 2008 and as recently as 2020. Relevant to this paper is A. Enrollments with reasonably high quality of information attached to them, including the total dollar amount of rental assistance provided, and

B. Enrollments where participants were placed into permanent housing during their enrollment. The following paragraphs detail the process of selecting a sample that fulfills these criteria, and Figure B.1 acts as a summary.

3.1 Sample Selection

Starting with data on Enrollments, the sample is limited to participants with a Move-In date between 2017 and 2019. The start is chosen based on when the HMIS system became ubiquitous for Rapid Re-Housing programs in LA County according to administrative documents (LAHSA 2017). The end is precautionary: The data spans activities through 2020, but a participant moving in late 2020 is likely to have rental assistance paid into 2021 where it is no longer observed. As such, the set is limited to move-ins before 2020, where only a minority might have assistance paid through 2021.

This analysis focuses on individuals labeled as "Head of Household" due to data limitations. The available data does not have any mechanism to group individuals by household, and most relevant information is tied to the Head of Household. A minority of observations were not included due to very young ages being listed. It is possible that these people (under 15 years of age) were mistakenly labeled as Head of Household.

The next round of cleaning concerns rental assistance entries. Like Enrollments, assistance entries are limited to after 2016 and before 2021. Remaining rental assistance entries are summed over a participant's enrollment in a project to create the response variable of interest, Total Rental Assistance (TRA). To screen for erroneous amounts of Total Rental Assistance, which are too high or too low to be accurately entered, a realistic window of average rental assistance per month must be established. HUD publishes what it considers "fair market rent", or FMR, annually for every United States county for studio apartments and for units with 1-4 bedrooms (HUD User). My lower bound is 75% of the lowest figure appropriate for this sample, 2017 FMR for a studio. The upper bound comes from the 2019 FMR of a 4-bed unit, multiplied by 125%.

Figure B.1: Sample Selection Process

Service Entries	
Rental Assistance service entries	84,191
Limited to service entries dated after 2016 and before 2021	83,817

Enrollments	
Enrollments in a Rapid Re-Housing program between 2008 and 2020	102,008
Limited to enrollments with a Housing Move-In Recorded between 2017 and 2019 (inclusive)	13,691
Limited to enrollments designated "Head of Household"	13,499
Limited to enrollments where age at entry was greater than 15.	13,486

Total Rental Assistance	
Service Entries aggregated by unique enrollment	13,983
Limited to aggregated amount greater than 75% fair market rent for studio in 2017 (>$741)	12,040
Limited to amount per month less than 125% fair market rent for 4-bed unit in 2019 (<$3,301.25)	11,838

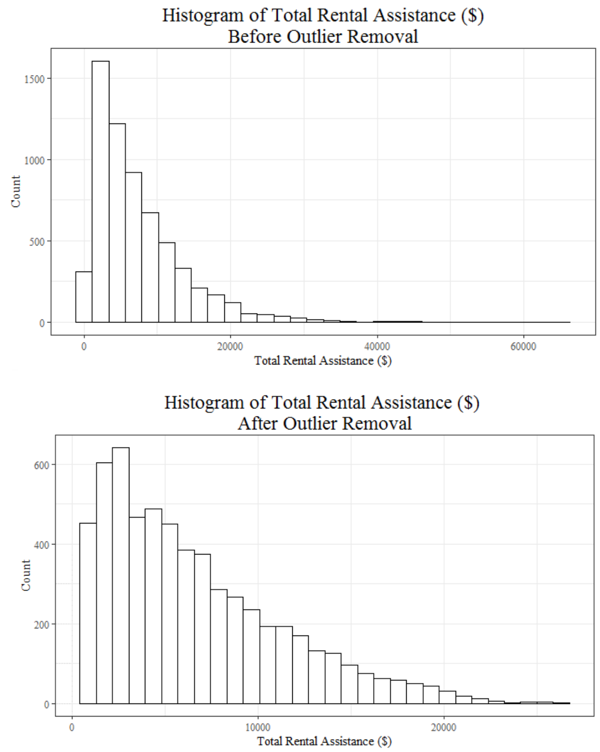
Final Observation Set: Enrollments ∩ Total Rental Assistance	
Final observations in the Enrollments table also present in the final Total Rental Assistance table	6,384
Limited to observations where the prior living situation is not missing	6,337
Limited to observations where the length of stay in prior living situation is not missing	6,256
Limited to observations where gender is not missing	6,237
Limited to observations with a Cook's Distance below 4/n	5,918

Final Observation Count	5,918

Average monthly Total Rental Assistance exceeding the upper bound is dropped. For observations with TRA below the lower bound, the decision to drop is based on the full sum rather than the monthly average. The reason is that a project that tapers assistance over time may pay less than the lower bound on average. For example, if a unit costs $1,000 in monthly rent, and the project subsidizes 100% the first month, 75% the second, then 50%, then 25%, the monthly average would by $625, while total assistance was $2,500. To capture enrollments where at least one month of assistance was provided near fair market rent, the full sum is compared to the lower bound rather than the average.

The final round of sample selection starts with the intersection of our sample of enrollments and our sample of TRA and three groups of observations are dropped due to missing information. With likely erroneous payments trimmed, the distribution of Total Rental Assistance is still heavily right skewed. In the interest of making the distribution better suited for modeling, a Linear Regression with all available predictive variables is estimated for the sole purpose of calculating Cook's Distance (Cook, 1977), and observations with a distance higher than 4/n (n being the total number of observations) are removed. This reduces the sample by approximately 5%, and most observations removed have a Total Rental Assistance of $20,000 or higher. This would be equivalent to a participant receiving rental assistance for 100% of their rent for over 11 months, using FMR for a two-bed apartment during 2019. Figure B.2 displays two histograms comparing the distribution of TRA before and after values are trimmed in this way.

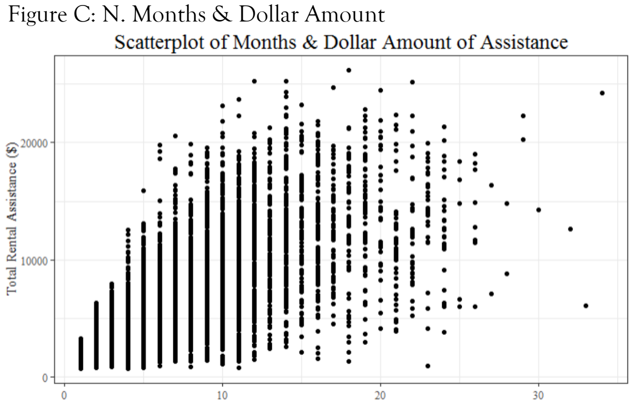
Figure B.2 - Results from Cook's Distance



3.2 Selection of Response Variable

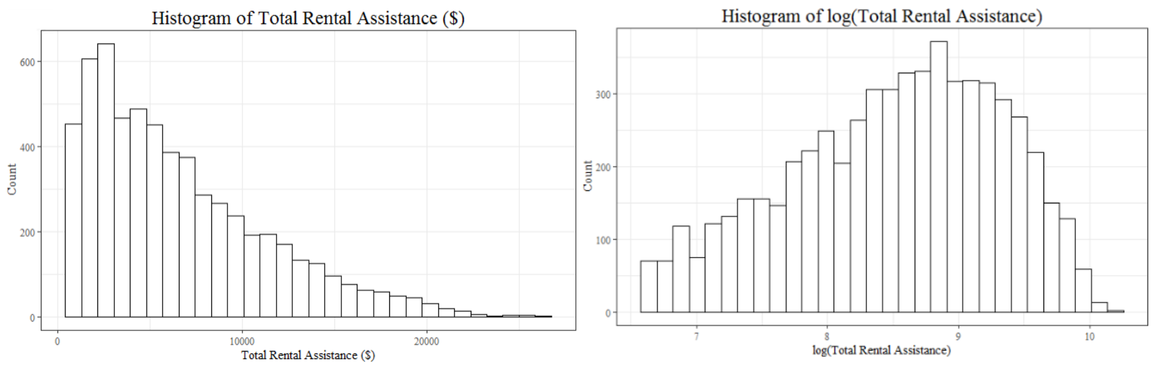
There are two promising candidates for measuring the amount of assistance a participant receives: One could examine the number of months a participant received rental assistance or sum the dollar amount of assistance. The two figures are strongly related with a 71% correlation coefficient between them. However, for any given subset of number of months, there is still considerable variation in the dollar amount of assistance. A subset with the most common number of months, 5, has a median $4,895 in assistance with a

Figure C: N. Months & Dollar Amount



standard deviation of $2,451. There is also a lot of overlap between most subsets of number of months: A sum of $10,000 in total assistance could realistically come from any number of months between 4 and 20. Figure C illustrates these points in a scatterplot. For these reasons, I believe the dollar amount gives a more accurate picture of how much a participant was assisted.

Figure D: Non-Transformed and Log-Transformed Total Rental Assistance



Once outliers are removed, the distribution of the response variable is still highly skewed, interfering with the estimation and interpretation of the linear regression model. No transformation approaches a normal distribution, but a log transformation is significantly less skewed. Log transformed TRA has a skewness of -0.360, significantly less than the untransformed skewness of 1.007. Regressions will be in the log-linear form for this reason. Figure D displays histograms of untransformed and log-transformed Total Rental Assistance.

This research recognizes two major categories of factors that influence the amount of financial assistance a participant might require to maintain private housing without a subsidy long term. The first are institutional, the second individual. Institutional refers to aspects like the size of the project

Table A.1: Numeric and Logical Predictor Variable

Variable	Class	Mean (% TRUE)	St. Dev.	Min.	Pctl(25)	Median	Pctl(75)	Max.
Age at Project Entry	Demographic	38	13	17	27	36	48	97
Monthly Income at Project Entry	Need	1,097	840	0	418	937	1,631	5,050
Number of Clients in Project	Institutional	68	49	1	29	52	110	184
Number of Projects by Provider	Institutional	7	3	1	4	7	9	11
Homeless in Prior Living Situation	Need	74%	-	-	-	-	-	-
Disabled	Need	23%	-	-	-	-	-	-
Veteran	Demographic	1%	-	-	-	-	-	-
Employed	Need	1%	-	-	-	-	-	-

an enrollment is associated with, or the geographic location the project operates from. Individual, for our purposes, is divided into demographic and need-based factors, examples being gender and income, respectively. Tables A.1 and A.2 break down value distributions for all variables that will be used in regression analyses.

3.3 Institutional Predictor Variables

We do not observe the amount of funding, nor the process a provider uses to decide rental assistance amounts (formula-based, case-worker discretion, etc.). There are two proxies that may shed light on these aspects. The total number of participants in a project is available and can give us an idea of how allocation decisions change with scale. A project with many participants may reduce the amount per participant to spread limited funds across more individuals. On the other hand, a larger operation may reduce their administrative costs per participant and can provide more direct assistance. Similarly, the number of projects managed by a provider may predict higher direct financial assistance, if administrative costs can be shared. In this sample the number of participants is highly variable, with a standard deviation of 49, or 72% of its mean. Some large projects are represented, with one having 184 participants moving into private housing and receiving rental assistance in a year (though not necessarily all receiving rental assistance at the same time).

Table A.2: Factor Predictor Variable Table

Variable	Class	Value	Percent
Service Planning Area (SPA)[1]	Institutional	*1*	9%
		2	12%
		3	7%
		4	13%
		5	9%
		6	28%
		7	9%
		8	10%
Length of Stay in Prior Living Situation[2]	Need	*<2 days*	4%
		2-7 days	5%
		>1 week	14%
		1-3 months	19%
		3-12 months	28%
		>1 year	28%
Race-Ethnicity[3]	Demographic	*Black*	55%
		Latinx	30%
		White	12%
		Other	3%
Move-In Year	Institutional	*2017*	29%
		2018	40%
		2019	31%
Gender[4]	Demographic	*Female*	65%
		Male	35%

[1]2% Multiple SPAs
[2]1% Unknown
[3]Other includes Asian, Native Hawaiian or Pacific Islander, or response missing
[4]0.4% identified as non-conforming

Each SPA a project is assigned to serve has a different population, particularly in terms of size. SPA 4 (containing Downtown Los Angeles) had approximately 16,000 homeless persons in 2019, the most out of any by far, while SPA 1, with cities like Lancaster, only had around 3,000. SPA was not an original data point in the original data but was imputed based on zip code of the project. There was only one project where a zip code could potentially refer to either SPA 4 or SPA 7. In this case, the greatest geographic overlap (SPA 4) was used. In 6 cases, projects were listed as operating out of multiple zip codes representing multiple SPAs. These were coded as "Multiple". There is a slight imbalance with SPA 6, which contains 28% of the participants in the sample. The second largest cohort is SPA 4 with 13%. This is not representative of the total homeless population of each SPA. SPA 4's homeless count in 2019 was nearly twice that of SPA 6 (LAHSA 2020).

All these aspects are plausibly influenced by time. Things like funding amounts, housing markets, and provider service philosophy can all change over our sample period. Therefore, the year of the move-in itself is included as a predictive variable. Further, both the number of participants in a project and the number of projects administered by a provider are both sub-indexed by the year a participant moved into a private residence and started receiving subsidies.

3.3 Individual Predictor Variables

Gender can be relevant in two ways; labor market outcomes and the likelihood of being a single parent, both aspects predicting that a woman may require higher amounts of assistance than a man. Self-identifying transgender and gender non-conforming persons are present in our data but make up a very minor segment (about 0.4%). For 0.3%, the response was missing. These observations were dropped. The common responses, female and male, make up 65% and 35% respectively. This is notable considering males make up slightly more than half of sheltered homeless, and almost three times as many unsheltered homeless (LAHSA 2020).

While we would hope Race and Ethnicity do not affect a provider's perception of a participant, labor or housing market discrimination could necessitate greater assistance for some identities. This measure has been simplified for this paper. In the original data, participants are asked to identify race from 4 options, Indigenous, Asian, Black, or White. Then they identify ethnicity as being Hispanic/Latin or Not Hispanic Latin. For this paper, if a participant selected Hispanic/Latin, this option supplants whatever option was selected for race. Indigenous and Asian populations have been aggregated into an "Other" category. The largest cohort is Black, at 55% of the sample.

Homeless in Prior Living Situation and the Length of Stay in Prior Situation are related and will be described jointly. Homeless in Prior Living Situation is an aggregation of a detailed question where a participant's living situation prior to their current situation is chosen from 25 possible responses, 3 of which fall under "Homeless Situations". This variable is coded as TRUE if the response is part of this umbrella and FALSE if it does not. In the regressions that follow it is strictly an interaction, with each category coded as TRUE if the participant was both in a homeless situation and the length of stay in this situation was for X timeline. The bins in Table A.2, with labels like 2-7 days or 1-3 months, are from the original data and is not an aggregation made for this paper (HUD 2020). Most participants (74%) report living in a homeless situation prior to project enrollment, and length of time is typically medium to long-term, with over half (56%) reporting living in that situation for at least 3 months.

Being disabled can mean more expenses, medical and otherwise, and a more difficult time in the labor market. On the other hand, for some physical disabilities a participant may be able to leverage other supports to their independence. The original survey given to participants asks about multiple conditions which can affect the ability to live independently. This includes physical disability, a mental health disorder, or substance use disorder, among others. Some conditions also have branch response to clarify if the condition is "expected to be of long-continued and indefinite duration and substantially impairs ability to live independently", while others are assumed to fulfill this criteria automatically (HUD 2020). If any of these categories are answered in the affirmative and longevity/impairment is fulfilled, this data point is coded as TRUE. Instances where this response is missing have been coded as FALSE, along with responses in the negative. At 23% being TRUE, disabling conditions are not ubiquitous but relatively common among those receiving services through Rapid Re-Housing.

3.5 Unavailable Predictor Variables

Actual housing cost would be useful. Our geography is Greater Los Angeles, and we cannot observe where in this large and heterogeneously priced area a participant is housed. Household size would also be useful. LAHSA (2020) reported that as of 2019, 15% of homeless persons in LA County are part of a family unit of more than one individual, so while observations like these are in the minority, the factor of family size is prevalent enough to be of interest. A family unit can plausibly require a larger amount of rental assistance for two reasons: They might require a larger and thus more expensive housing unit, and the additional expenses associated with taking care of children might mean the responsible adult needs more financial assistance with rent and for a longer period. Unfortunately, our data does not contain information on family sizes, and this no doubt important dimension cannot be explored.

HMIS systems retain the ability for monthly income to be updated periodically in such a way that an analyst can observe changes over time (HUD 2020). However, in this sample, income updates are rarely recorded, and it is unclear if this represents the true state of participants. 58% of participants have no update to their income recorded. For this reason, only income at project entry is incorporated into this analysis.

4. Regression Analysis

To better understand variability in rental assistance amounts, in particular examining how providers respond to participant needs, and how influential external factors are, my approach is to use HMIS Administrative data on observable potential determinants in a linear regression framework. The first goal is to assess which observable determinants are most influential. Second is to assess the importance of unobservable factors. The model used to explore the relationships between observable factors and total rental assistance takes the following form:

$$\log(Y)_i = \mu + \boldsymbol{\beta_1 X_{1i}} + \boldsymbol{\beta_2 X_{2i}} + \boldsymbol{\beta_3 X_{3i}} + \epsilon_i$$

Where Y_i is the total rental assistance received within a single enrollment i. $\boldsymbol{\beta_j X_{ji}}$ represents observable characteristics of institutions ($j = 1$), participant demographics ($j = 2$), and participant need ($j = 3$), $\boldsymbol{\beta}$ is a vector of weights applied to characteristics $\boldsymbol{X_i}$ for enrollment i. ϵ is unobservable factors, in particular the decision-making processes internal to projects.

4.1 Regression Estimates

The most significant finding from the regressions is that, as a person facing homeless and offered Rapid Re-Housing services, the project you are assigned based on your SPA and population type has the most observable influence on the amount of assistance you'll receive. The simplest model with institutional variables only (Number of Participants in Project, Number of Projects by Provider,

Table B: Factor Predictor Variable Table

Log-Linear Regressions

	Dependent variable:			
	log(Total Rental Assistance)			
	(1)	(2)	(3)	(4)
Number of Clients in Project	0.002***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of Projects by Provider	0.01**	0.02***	0.01***	0.02***
	(0.004)	(0.004)	(0.004)	(0.004)
Move-In Year: 2018	0.21***	0.19***	0.21***	0.19***
	(0.03)	(0.03)	(0.03)	(0.03)
Move-In Year: 2019	0.36***	0.32***	0.35***	0.31***
	(0.03)	(0.03)	(0.03)	(0.03)
SPA: 2	0.78***	0.72***	0.73***	0.69***
	(0.04)	(0.04)	(0.04)	(0.04)
SPA: 3	0.48***	0.49***	0.41***	0.44***
	(0.05)	(0.05)	(0.05)	(0.05)
SPA: 4	0.57***	0.55***	0.52***	0.52***
	(0.04)	(0.04)	(0.04)	(0.04)
SPA: 5	0.75***	0.71***	0.73***	0.70***
	(0.05)	(0.05)	(0.05)	(0.05)
SPA: 6	0.64***	0.61***	0.61***	0.59***
	(0.03)	(0.03)	(0.04)	(0.04)
SPA: 7	0.38***	0.34***	0.34***	0.32***
	(0.04)	(0.05)	(0.04)	(0.05)
SPA: 8	0.60***	0.56***	0.57***	0.55***
	(0.04)	(0.04)	(0.04)	(0.04)
SPA: Multiple	0.75***	0.69***	0.70***	0.66***
	(0.06)	(0.06)	(0.06)	(0.06)
AIC	13615	13459	13581	13434
Adjusted R^2	0.11	0.14	0.12	0.14

	(1)	(2)	(3)	(4)
Gender: Male		-0.16***		-0.16***
		(0.02)		(0.02)
Gender: Other		0.28***		0.30***
		(0.09)		(0.09)
Race-Ethnicity: Latinx		-0.01		-0.004
		(0.02)		(0.02)
Race-Ethnicity: White		-0.01		0.001
		(0.03)		(0.03)
Race-Ethnicity: Other		0.06		0.06
		(0.06)		(0.06)
Age at Entry		-0.01***		-0.01***
		(0.001)		(0.001)
Veteran		-0.10		-0.10
		(0.08)		(0.08)
Disabled			-0.04*	0.004
			(0.02)	(0.02)
Employed at Entry			0.09***	0.05**
			(0.02)	(0.02)
Monthly Income at Entry			0.0000	0.0000
			(0.0000)	(0.0000)
Homeless in Prior Living Situation			0.19***	0.20***
			(0.05)	(0.05)
Prior Homeless Situation: 2-7 days			-0.08	-0.08
			(0.07)	(0.07)
Prior Homeless Situation: >1 week			-0.07	-0.08
			(0.05)	(0.05)
Prior Homeless Situation: 1-3 months			-0.12**	-0.12**
			(0.05)	(0.05)
Prior Homeless Situation: 3-12 months			-0.08	-0.07
			(0.05)	(0.05)
Prior Homeless Situation: +1 year			-0.13**	-0.08*
			(0.05)	(0.05)

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Move-In Year and SPA) explains about 11% of variation in total rental assistance, according to the adjusted R^2 score of the model. Adding demographic controls (Gender, Race, Age and Veteran status) only increases explanatory power by 3%, and variables associated with direct, immediate need for assistance, such as prior living situation, disability and employment do not perceivably improve explanatory power at all. This was not an expected result, considering projects should be responding to individual needs. While a linear regression does not show definitively that they are not, it is surprising that higher-level characteristics seem much more relevant. Table B. displays regression results with four different combinations of institutional, demographic, and need-based variables. As seen in Figure E., regression errors are heteroscedastic and show a pattern of increasing with higher predictions for Total Rental Assistance (TRA). A Bruesch-Pagan test clearly rejected the null hypothesis for homoscedastic errors, well within 0.001 confidence level. For this reason, all standard errors are White's Heteroscedasticity-Consistent Errors (White, 1980).

Using SPA 1 as our base case and taking standard errors into account, being served in SPA 2 or SPA 5 is associated with receiving between approximately 85 and 65% more financial assistance, depending on which controls are utilized. The middling case is SPA 4, associated with a 61-48% bump in assistance. While any SPA compared to the base case predicts a dramatic spike in TRA, comparisons between SPA coefficients are significant, though much more moderate. The difference between any SPA coefficient and its closest neighbor in magnitude is on average 0.7 on average, and between the 2nd closest neighbor is 0.13. To that end, it's useful to think of TRA by SPA as having 3 "clusters"; low (<0.50) medium (0.50-0.65) and high assistance (0.65<). This clustered ranking is consistent regardless of controls. Table C.1 summarizes these clusters.

Figure E: Log-Linear Regression Residual v. Fitted Values

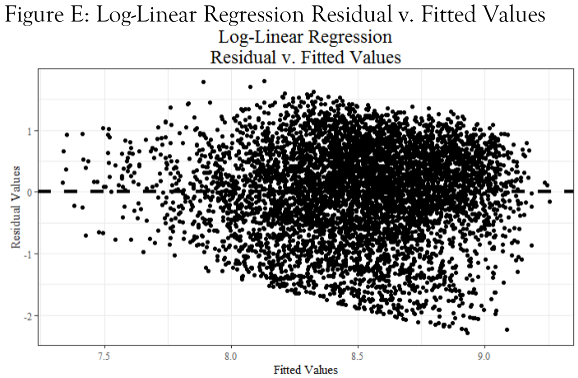


Table C.1: Service Planning Area Clusters

Cluster	SPA	Coef. Range
High	5	0.70-0.75
(0.65<)	2	0.69-0.78
Medium	6	0.59-0.64
(0.50-0.65)	8	0.55-0.60
	4	0.52-0.57
Low	3	0.41-0.49
(<0.50)	7	0.32-0.38
	1	Base (0)

This high importance warrants a review of what is wrapped up in a SPA: Funding amounts, provider/project decision, and different homeless populations (most observably in size, but possibly different in other aspects). Focusing on the aspects that we can observe, I use Point-In-Time counts released by LAHSA and full population counts by County of Los Angeles Public Health and calculate the correlation coefficient between these coefficients and either the nominal count or the ratio of homeless. SPA 1 is treated as having a coefficient of 0 for this purpose. The correlation coefficient between the ratio of homeless and the SPA regression coefficients is between 0.05 and 0.08. The same metric, but using the nominal count, is between 0.43 and 0.45. Table C.2 displays these relationships. It is not definitive if funders or providers are responding to differences in the size of homeless populations in different areas, but if they are it is to the raw count, not the concentration. While it is plausible that the response is to housing market tightness and different rent prices, it is not certain if participants are typically finding housing in the same SPA they are being served in.

Table C.2: Correlation of Population & Regression Coefficients

Corr. with Regression Coefficients	**(1)**	**(2)**	**(3)**	**(4)**
Homeless Ratio	0.05	0.06	0.07	0.08
Homeless Point-In-time	0.45	0.45	0.43	0.44

The coefficient associated with the number of participants in the project is positive and very robust to different controls. Its positive association contradicts the idea that projects serving more participants will spend less per person. I propose two possible explanations that are not mutually exclusive: The first is that projects with more participants are able to devote more funds to direct assistance with economies of scale, where administrative costs per participant go down. The second is that projects with more participants could have a funding premium over other projects that outpace the higher number of persons. The explanation of fund allocation between administration and direct assistance also applies to the positive relationship between the number of projects a provider is simultaneously managing and the amount of rental assistance.

To illustrate the effect of participant scale, I'll use the 25^{th}, 50^{th}, and 75^{th} percentile values of the number of participants as examples, calculating from the shared coefficient and standard deviation from regressions (2), (3), and (4).

- 25^{th} perc. (29): 2.3 – 3.5%
- 50^{th} perc. (52): 4.2 – 6.2%
- 75^{th} perc. (110): 8.9 – 13.2%
- Max value (184): 14.7 – 22.1%

This effect is much more economically relevant when applied to higher percentiles. At the 75^{th} percentile of 110 participants, the effect is similar in magnitude to the effect of being served in a high-assistance SPA cluster over a lower cluster.

Most relevant to demographics is gender, particularly the male identity. Being a male participant is associated with receiving 16% less rental assistance on average. There could be bias taking place, or males in this sample could have better labor market outcomes and therefore require less assistance. However, this estimate is robust to controlling for income at entry, so if males are having an easier time finding work, it is after their initial intake into a project. In addition, females may disproportionally be single parents with responsibility/custody over children, incurring higher expenses and requiring more assistance.

Age is associated negatively with the amount of assistance needed, and the coefficient in this regression is very convenient to interpret. Each year of age is associated with a 1% decrease in the amount of rental assistance the participant receives. At the 50^{th} percentile of 36 years of age, this predicts 36% less assistance compared to a person at the minimum age of 17. It is possible that older individuals, even those experiencing homelessness, have higher human capital and with stability afforded to them through a Rapid Re-Housing program, can find work faster and therefore require less assistance. It's also worth factoring in that older participants can access other supports like social security and may require less financial assistance from Rapid Re-Housing as a result.

Coefficients for Race-Ethnicity are insignificant, both economically and statistically. African American identity was chosen as the base value, since this demographic is most common in the sample. While this does not mean there is no racial discrimination in Rapid Re-Housing projects, it isn't detected on the dimension of the amount of rental assistance using linear regression. This does not rule out other possible scenarios, such as discrimination during the housing search.

To reiterate, the last class of variables, need-based, provides no perceivable improvement in the explanatory power of the model, but some individual variables have interesting effects. It appears that a participant being homeless in a previous living situation predicts an assistance premium around 20%, depending on controls. The interactions with length of time homeless are more nebulous. The most reliable effect (-12%) is associated with being in the prior homeless situation for 1-3 months. The same type of effect for over 1 year (-13%) is similar but becomes much smaller when controlling for demographics. Either way, the trend is puzzling. This paper does not have a strong hypothesis as to why 1-3 months have a more significant effect than both lower and higher amounts of time

5. Limitations & Future Work

Adjusted R^2 ranges between 11-14% in the log-linear regressions used here, which is fairly low. An assumption of the model is that errors ϵ are primarily driven by case worker decisions and provider-level management guidance. It is unlikely that case worker and management decisions account for 85% or more of assistance amounts. However, the predictive power of the model was mainly driven by differences between SPAs, and there is some overlap between SPA and provider characteristics, such as populations being served and higher-level funding allocation. Future work should focus on distinguishing between effects from SPAs and effects from providers. One example of this would be to collect funding amounts per SPA, which are publicly available and plausible to collect with some effort. This may increase explanatory nuance and reduce the amount of variance attributed to caseworker decisions.

Outside of institutional characteristics, several individual-level predictive factors not discussed in this paper would be good candidates for examination in future work. Household size likely has a lot of influence and would be a useful variable. Optimally this would be broken down to the number of adults and children in each unit, accounting for the fact that adults can be additional sources of income, while children would be expected to increase expenses. It could also be useful to break up some of the broad indicators used in this analysis, for example using more nuanced categories of disability rather than aggregating them into one indicator.

Zooming out to the broader experiment design suggests other avenues for future work. Echoing previous ideas on SPA and provider distinction, using provider or project level fixed or random effects would be straightforward and worth attempting. One could also model separate regressions for each SPA. Another proposition is to graduate from the simple linear regression model and attempt a generalized linear model better equipped to examine a variable with the high skew seen in Total Rental Assistance.

6. Conclusion

In this paper, I gave an overview of how Rapid Re-Housing functions and where it fits into the wider issue of homelessness in the United States. Using linear regression, I sought out the most meaningful factors related to rental assistance amounts within RRH projects in Los Angeles and reported on their implications. I found that characteristics of providers and spatial variation are the most important factor in predicting rental assistance amounts, and that these proxies are partially related to the nominal number of homeless individuals in each SPA. Rather than being mostly dependent on observable characteristics of the participant, my results imply that assistance amounts depend more on where the provider operates and its internal service philosophy. It is also implied that assistance amounts may not be systematically related to client needs, and therefore research on effectiveness should not treat Rapid Re-Housing as a homogenous treatment.

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