The Staying Power of Resident Services

A Time to Event Analysis of Mercy Housing Residencies

By Benjamin Gowan

Mercy Housing National Resident Services Program Evaluation

2019

Contents

Introduction

We are biased, and as a statistical analyst, it is always important to acknowledge that. We are guided by Mercy Housing's mission statement, as it is the core of this analysis:

To create stable, vibrant, and healthy communities by developing, financing, and operating affordable, program-enriched housing for families, seniors, and people with special needs who lack the economic resources to access quality, safe housing opportunities.

The program-enrichment referenced here are services provided onsite to residents — Resident Services. These are the core of what we analyze as the National Resident Services program evaluation. These Resident Services span several key program areas, including health and wellness, community participation, out-of-school time (for children), financial stability, and specifically housing stability. These priority program areas each have a special focus, but all contribute to the overall Mercy Housing mission of quality, safe housing opportunities that we strive to fulfill.

The Key Question

A key question we want to ask ourselves is whether residents who participate in our Resident Services stay housed longer with Mercy Housing, compared to those who did not participate in these services. Specifically, in this analysis we explore the association between **household participation** in services and **length of residency**, in terms of any move-out and then more specifically residencies that ended in a negative move-out (eviction or abandonment scenarios that we actively seek to prevent and have Resident Services specifically designed for). Services are included simply in terms of any household participation, if members participated in any Resident Services prior to the occupancy end date (service delivery as a time-varying continuous term may be examined in a subsequent analysis).

A Brief Primer on Survival Analysis

This type of study, where we examine the risk of an event over time, has several names, including 'survival analysis,' 'time to event analysis,' 'time to failure,' and more. A critical aspect of this kind of analysis is the inclusion of a whole observable sample, not just those who experience the event we want to study. If we want to calculate the risk of something happening in a population over time, say the risk of getting a speeding ticket for example, we cannot simply look at those who got a speeding ticket and see how long it took for that to happen. This would dramatically overestimate the risk and underestimate the time for it to typically happen in the general population. If you'd like some helpful details on this type of data, please see the appendix on censoring.

How This Analysis Was Prepared

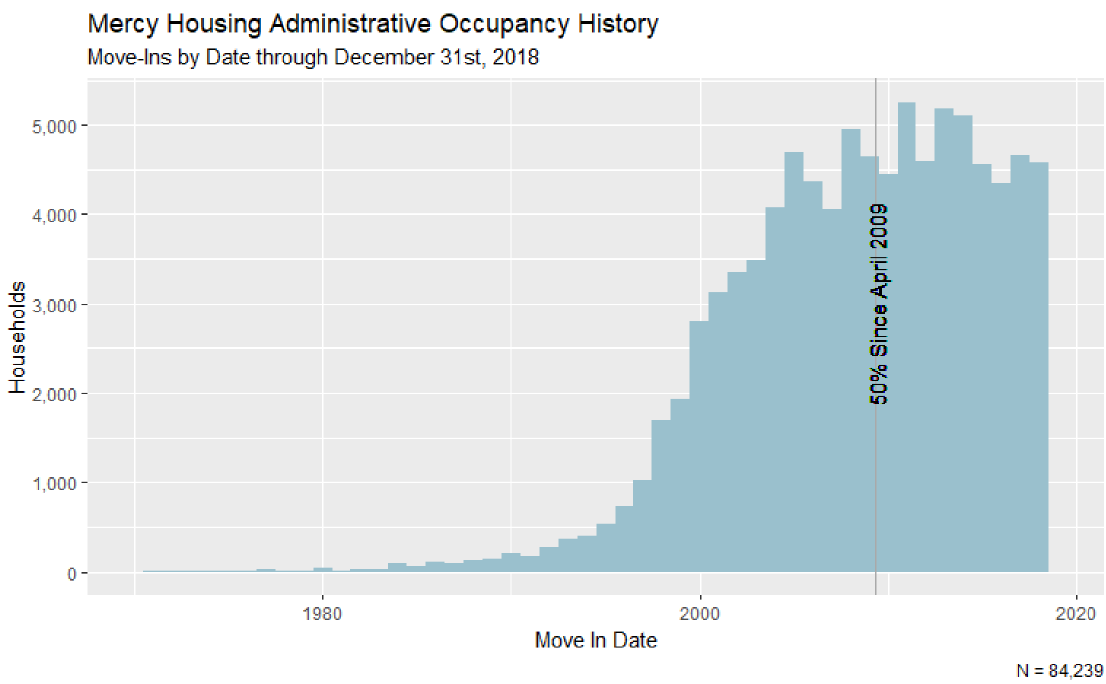
The Data

This analysis uses administrative data for resident occupancies and service delivery. To apply proper survival techniques to this type of data we need to impose artificial boundaries to mimic what an accurate study, from an outside source, would be like and address the censoring issues we previously noted in the introduction. To do that, we first looked at the spread of our data and let that inform how far back we should go, how long our observation window should be, as well as which properties can reasonably be included.

Residency History

Administrative occupancy data for Mercy Housing goes back nearly 50 years, with the earliest residencies in 1970. That is only a year after the moon landing! This is in fact, before Mercy Housing itself started, as residency history is brought along with residents for buildings that are acquired. Through the end of 2018 this data covers nearly 85,000 unique residencies. However, Mercy Housing has grown substantially over time, especially in recent years, such that the majority of all move-ins have occurred in the last decade (half since just April 2009).

Figure 1A

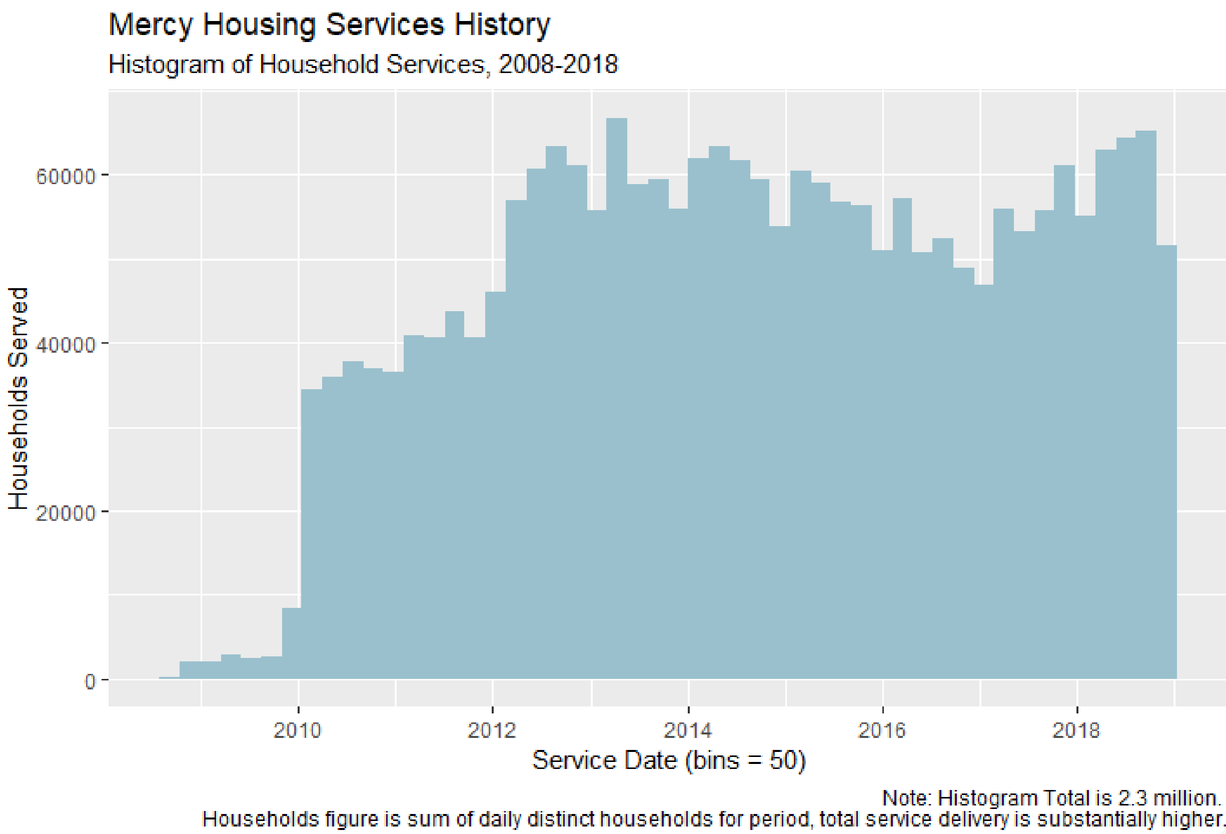


We want our analysis to apply to Mercy Housing as it exists today, so we focus on residencies that have occurred in the past decade. There has been growth and change in that time period, but the population is fairly stable over that time compared to the 1990s or early 2000s where property and population growth was immense. The past 10 years of data are more reliable and more applicable to the current Mercy Housing population.

Service History

Mercy Housing service data also has a rich history, though electronic record keeping of it is more recent. Resident Services tracking for our modern system began piloting in late 2008, fully gaining traction in 2010.

Figure 2A



The scale here is somewhat different than the occupancy data. Every day in this Resident Services data the entire current resident population could possibly receive a service. This is a histogram, where 10 years of data has been divided into 50 bins, where the number of daily distinct households that received services are summed up over that 'bin' of time. This may seem high, but this is substantially less than total Resident Service delivery (households often receive more than one Resident Service in a day, but we are only counting them once).

Negative Move-outs History

As a final pre-data-preparation step, we look at the timeline of negative move-outs. **Remember we cannot solely look at evictions in our analysis, this is not our analysis dataset.** However, here we briefly look at only evictions to see their typical length of residency to make sure that our data preparation properly captures a representative sample.

If we look at the past 20 years of residencies that have ended in an eviction or abandonment, we find that 75% of evictions/skips occurred by 3.29 years into the residency. Further, 86.3% of all evictions/skips in this period occurred by five years of residency. Finally, we know that reliable services data would only allow for a maximum residency length of about eight years at the longest possible residencies.

Figure 3A

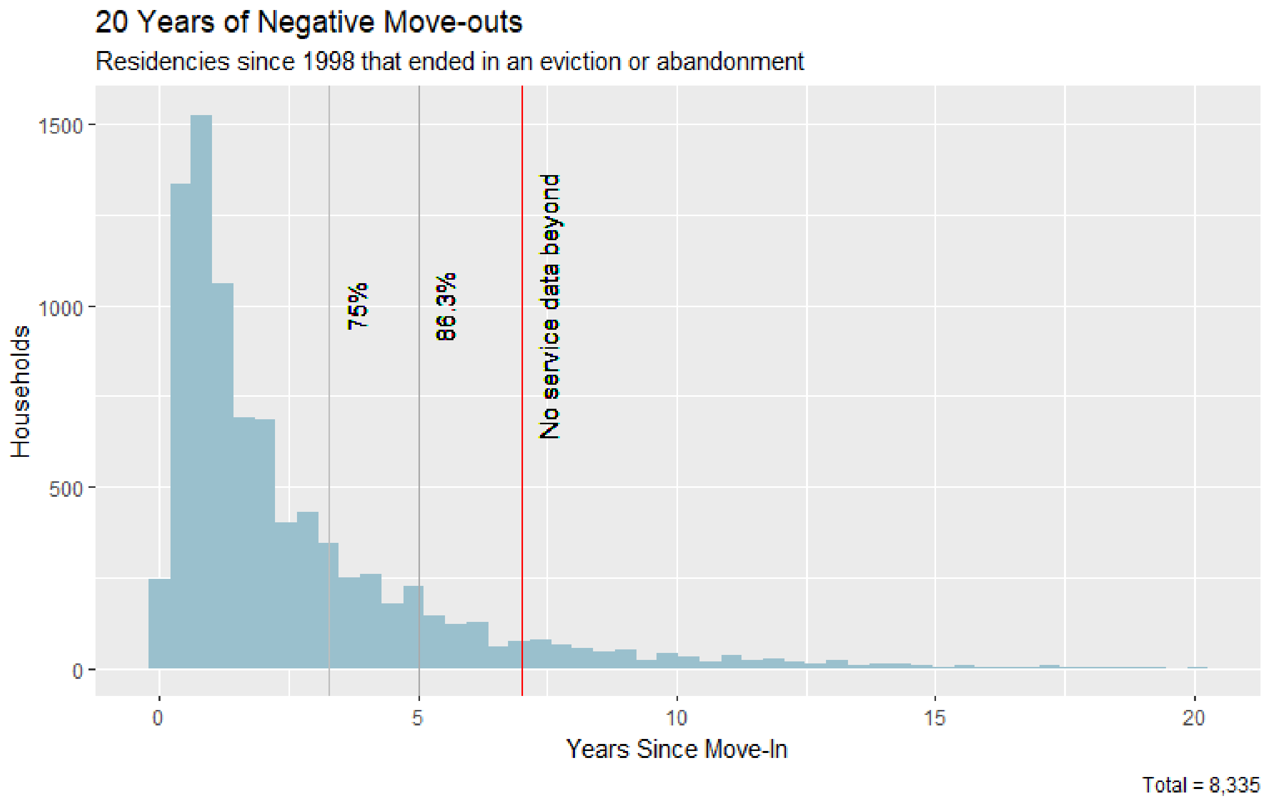


Figure 3A introduces an important concept of how we look at time in survival analysis. Our data includes households that *moved-in* over years, but when examined together, we pretend everyone *moved-in* on the same day, and time refers to the time since *move-in*.

Further, if we compare our *move-in* history for the same 20-year date range, we get our first measure of prevalence, showing that there is a crude rate of 9.57% of *move-ins* ending in a negative move-out over this 20-year period.

Analysis Data Selection

With the previously mentioned data in mind, the following parameters and filtering were applied to occupancy and services data to producing an analysis dataset:

Property Selection Criteria

- Senior properties were excluded because move-outs and evictions are quite rare while also having high service delivery. This would unfairly bias the analysis in favor of Resident Services.
- Only properties with Resident Services were included and only for the period while services were actively delivered at the property (i.e., sometimes properties gain or lose Resident Services.)
- Properties had to have at least five negative move-outs after all other data selection criteria had been applied.

Residency Selection Criteria

- Occupancies that **started** between January 1, 2010 and December 31, 2016.
- Occupancies could **end** any time after January 1, 2010 through December 31, 2017. (This allows for a possible year of observed residency for those move-ins that occur late in the move-in window).
- The ‘follow-up’ time window of interest is through five-year residencies.
- In the all move-outs analysis unobserved move-outs (did not move-out prior to December 31, 2017) are right censored.
- In the negative move-outs analysis only evictions and abandonments are events, and all other move-outs or un-ended residencies are censored (please see appendix for further information on censoring if curious.)

Description of Analysis Dataset

After all selection criteria has been implemented, which are all attempts to remove biases from the analysis, we get the following dataset:

Figure 4A

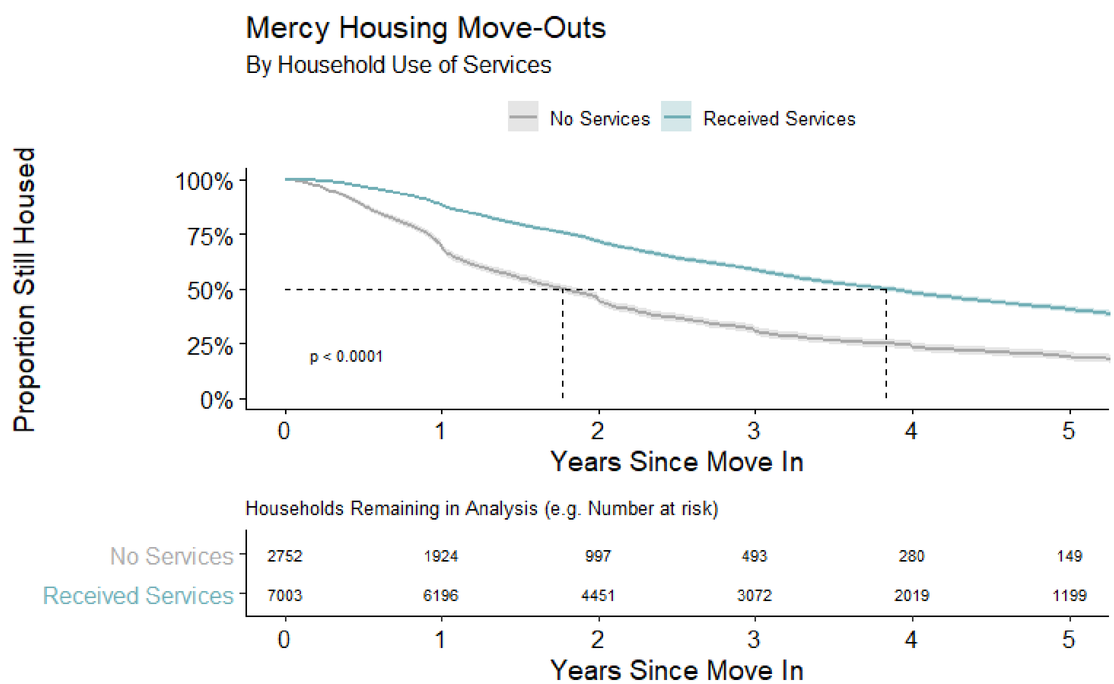
Data Summary	Count (%)
Total Residencies	n = 9,755
Resident Services	
Households with No Services	2,752 (28.2%)
Received that Received Services	7,003 (71.8%)
Negative Move-Outs	
Abandonment or Eviction	1,847
Population Served	
Family	6,925 (71%)
Supportive Housing	2,830 (29%)
Region	
MHC	2,564 (26.3%)
MHLF	2,037 (20.9%)
MHMP	1,811 (18.6%)
MHNW	1,159 (11.9%)
MHSE	2,184 (22.4%)
Properties	
Family	50
Supportive Housing	23

We have an analysis dataset of 9,755 residencies, with a good representation across major population groups. Further, we see that we have included 73 properties, substantially fewer than the number of properties with services. This is because not all properties had a sufficient number of evictions to be included in the analysis (including properties with few evictions but regular services may unfairly advantage the service participation group).

The Analysis

All Move-outs Analysis

Figure 5A



In our first look at the outcome differences by raw participation in Resident Services, we can see that *length of residency* is substantively longer (statistically significant). The dashed lines in Figure 5A show *median survival* that is the length of residency that 50% of the group makes it to before *move-out* or *censure* (in this case making it to the end of the observation window).

Fewer Move-outs Than Expected Among Service Users

If we take this same unadjusted data and look at the difference in expected *number of move-outs* by service group, we get the following results:

Figure 6A

Mantel Haenszel Log-Rank Test

Resident Services	Total Households	Observed Move-Outs	Expected Move-Outs	Difference
No Services	2,752	1,903	1,092	811
Received Services	7,003	3,666	4,477	-811

This is a basic statistical test, effectively a chi-square of our data, and it shows the difference in *observed* versus *expected number of move-outs* between households that participate in Resident Services versus those which did not. It suggests that in this scenario about 800 (18%) fewer *move-outs* occurred in the services group than expected. That is, of course, a very encouraging result!

A Simple Introduction to Survival Adjustment

However, the caveat that this is 'unadjusted' data, means we are not considering several factors that might be affecting this result. For example, we have a lot more data earlier on in residencies versus later on, perhaps we would want to adjust for that. We can, in fact, do that with a very similar test which weights for the number of households left in the analysis at each point in time.

Figure 7A

Peto and Peto Gehan-Wilcoxon Test

Resident Services	Total Households	Adjusted Observed Move-Outs	Expected Move-Outs	Difference
No Services	2,752	1,464	811	653
Received Services	7,003	2,393	3,045	-653

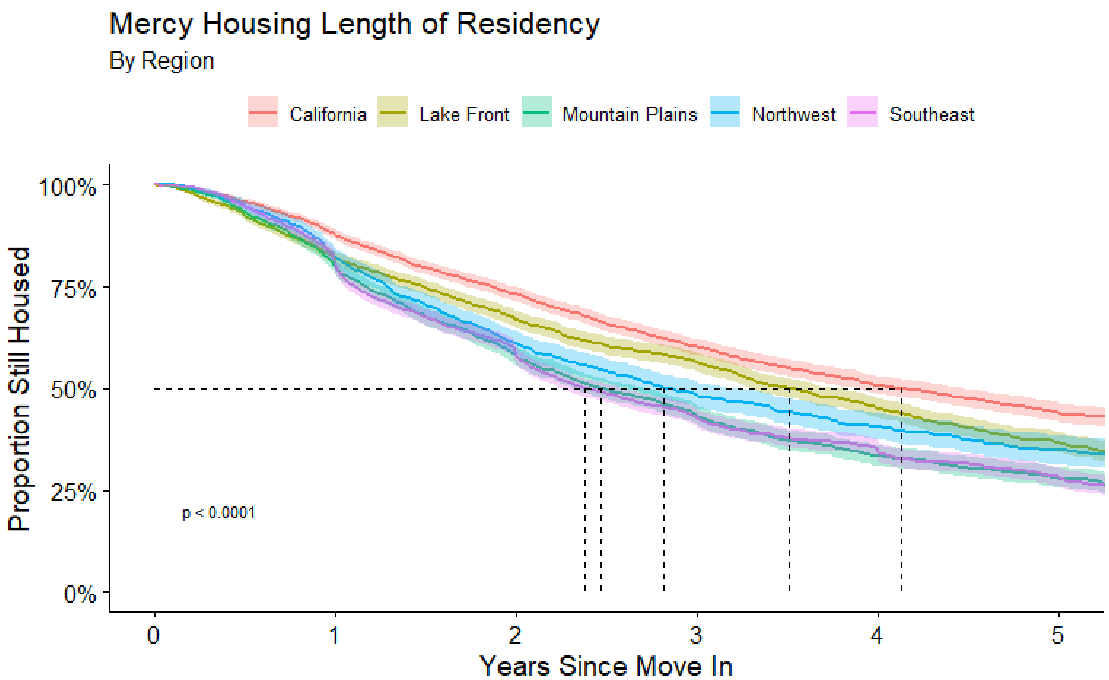
With this adjustment, we ensure we are accounting for the drop-in data over time (and for reference, potentially non-proportional hazards between the groups). We should note the results are a little more difficult to interpret now, because we are not using the raw data, but this can be a very helpful process in Figure 7A. The association between *Resident Services* and *move-outs* actually got stronger with the adjustment: about 650 fewer *move-outs* than expected were observed, but this out of an adjusted number of expected and observed events, 2,392/3,045, so 21.4% fewer than expected. So, we had an initial encouraging result but then went a step further to be more rigorous about that by adjusting for a known imbalance in our data over time. This is the basic gist of statistical adjustment, weighting or averaging or in some manner transforming our raw data in order, in an attempt to remove any influence, it may have on results.

In the data, there is much more we need to take into account as far as possible differences that could be skewing our analysis. These residencies are taking place in very different situations, such as different regions, types of housing, and at a very basic level, different properties. And we can readily see that these groups are all quite different in terms of unadjusted length of residency.

Sub-populations Have Substantial Differences

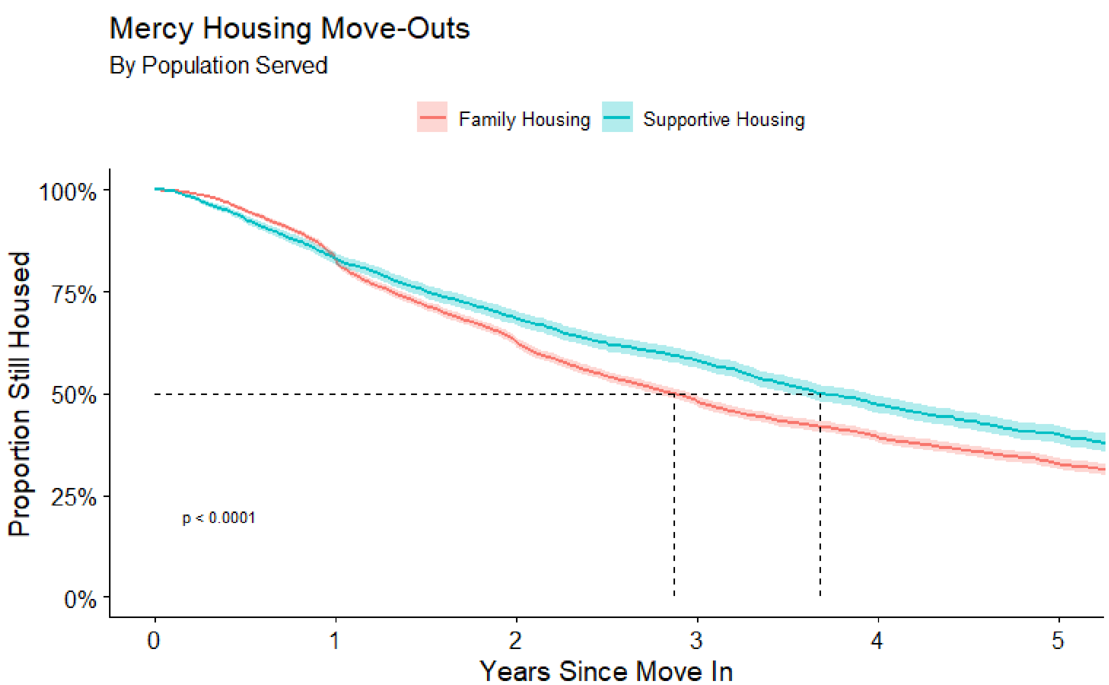
Region

Figure 8A



Property Population Served

Figure 9A



As we can see there are substantive differences by region and population in Figure 8A and 9A. There are also individual property differences, but visualizing over 70 properties is quite challenging. The goal here is not to make statistical comparisons by region; rather we're simply confirming and acknowledging that these differences exist. (There is also a technical issue here that we won't explore, which is that for *population served* the hazards are clearly non-proportional as they cross in time).

Final Move-Outs Cox Model

To simultaneously account for all these differences that could be impacting our results we will fit a statistical model called a Cox Proportional Hazard model. This means that adjusting for key differences, we've noted in our sample populations, we'll compare the *hazard* of households that participated in services versus those that did not. So far, we have been looking at the *survival* curve, which is the probability a household will still be housed at a point in time. Similarly, *hazard*, in this context, means the instantaneous (i.e., not cumulative) risk for the remaining households at a point in time. When we look at the results of a Cox model, we'll get a single value, a *hazard ratio*, that tells us how much more or less risk our services group has of *move-out* compared to the non-services group.

When we take into account all the above-noted differences, we get the following final all *move-outs* model:

Figure 10A

Mercy Housing Any Move-out Cox Proportional Hazard Model

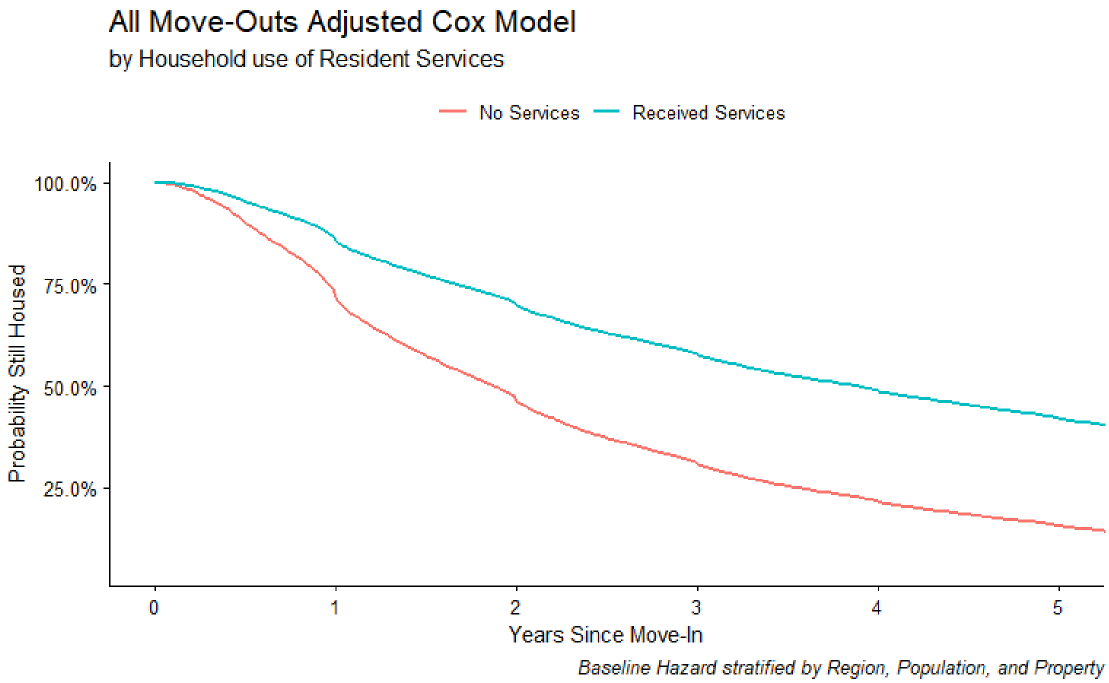
Resident Services	Hazard Ratio (Confidence Interval)
Household Received Services	**0.48** (0.45-0.52, $p<0.001$)

Note: Hazard stratified by region, population served, and property

What Does This Mean?

This means that accounting for differences between regions, populations, and at each property, we still see that households which participated in Resident Services had 52% *less hazard* (risk over time) of any move-out than those that did not. This is a remarkably robust finding based on over 9,500 residencies, accounting for major confounding variables, and is a difference that was present in unadjusted and adjusted testing.

Figure 11A



Note: Model 11A demonstrates the *difference in housing stability* associated with Resident Services for a specifically selected high turnover subset of properties (recall from the data preparation section that senior properties and properties with fewer than five evictions were omitted). The relatively low probabilities of making it past five years shown here are not meant to be extrapolated to the overall Mercy Housing resident population. Rather, it is showing the robust protective association of resident services even in higher hazard scenarios.

Negative Move-Outs

This has been an informative and encouraging analysis, but we want to go one step further. We want to specifically analyze *move-outs* that are clearly negative. There are a few reasons for this, one is that some *move-outs* may actually be positive, and we want to ensure we are not counting those as a negative outcome (for example a small percentage of residents move-out to purchase homes, which is an excellent outcome).

We can use this same modeling data set, but we define our outcome of *negative move-outs* as evictions or abandonments. These are negative for both residents and Mercy Housing. Further, sometimes abandonments are pre-emptive to formal evictions, as the resident realizes that is forthcoming and wishes to avoid the process. We consider other *move-outs* as normal and right-censored. We will briefly run the same analysis steps we just walked through.

Fewer Than Expected Negative Move-outs Among Service Users

Figure 12A

Mantel Haenszel Log-Rank Test

Resident Services	Total Households	Negative Move-outs	Expected Negative Move Outs	Difference
No Services	2,752	670	373	297
Received Services	7,002	1,177	1,474	-297

In the raw unadjusted test, we see that negative move-outs have 20.1% fewer than expected in the services group.

Peto and Peto Gehan-Wilcoxon test

Resident Services	Total Households	Adjusted Observed	Expected Move Outs	Difference
No Services	2,752	615	337	278
Received Services	7,002	1,014	1,292	-278

The time-weighted adjusted test improves the reduction of observed versus expected negative move-outs to 21.5%.

Mercy Housing Negative Move-Outs Cox Proportional Hazard Model

Resident Services	Hazard Ratio (Confidence Interval)
Household Received Services	**0.59** (0.52-0.67, p<0.01)

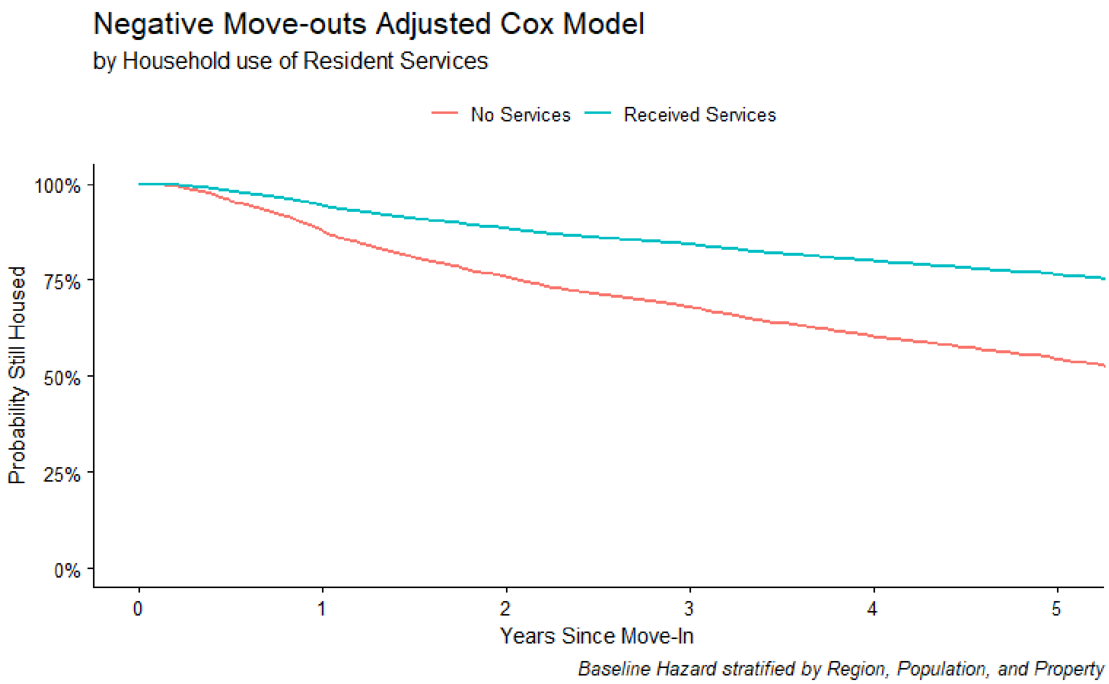
Note: *Hazard* stratified by region, population, and property

What Does This Mean?

This means that accounting for differences between regions, populations, and at each property, we still see households which participated in Resident Services had 41% *less hazard* (risk over time) of *negative move-outs* (eviction and abandonment) than those that did not.

This is slightly attenuated, but a similarly robust finding as the general *move-outs* analysis and is based on the same dataset of over 9,500 residencies, accounting for major confounding variables, and is a difference that was present in both unadjusted and adjusted testing.

Figure 13A



Service Type

A final question to explore is the independent effect of each service type on overall length of residency and negative move-outs. We cannot rely on some of the simpler tests we have seen because we have a lot more variables to consider. If we keep services represented as a simple *yes/no* variable, with five priority program areas and one cross-cutting services group (such as transportation assistance and technology literacy that are broad support services) we would have more than 60 levels in a log-rank test for this dataset. Further, since each service area is a comparison of participation versus no participation for that specific group of services, a graph of the adjusted model with all the services would have a dozen lines, which is too difficult to interpret meaningfully. So, we will jump to a summary of the *hazard ratios* for each priority service area for overall length of residency and negative *move-outs*.

Figure 14A

Mercy Housing Priority Program Areas Cox Proportional Hazard Models

Services Received	General Residency HR	Negative Move-Outs HR
Community Participation	0.60 (0.55-0.65, p<0.01)	0.55 (0.47-0.64, p<0.01)
Cross Cutting Activities	0.71 (0.64-0.77, p<0.01)	0.72 (0.61-0.84, p<0.01)
Financial Stability	0.90 (0.82-0.99, p=0.03)	0.73 (0.62-0.86, p<0.01)
Health and Wellness	0.73 (0.67-0.80, p<0.01)	0.79 (0.68-0.92, p<0.01)
Housing Stability	0.76 (0.70-0.83, p<0.01)	1.23 (1.07-1.42, p<0.01)

Out of School Time	1.06 (0.96-1.16, p=0.23)	0.98 (0.82-1.16, p=0.8)

Note: hazard stratified by region, population served, and property

We have some very interesting results from Figures 13A and 14A. First, we can note that nearly all service areas are **independently**, significantly associated with less risk of a *general move-out* or a *negative move-out*. Meaning that, for example, community participation is associated here with 45% *less hazard* of a negative move-out, even after taking into account other services, like financial stability or health and wellness.

There are two exceptions. One is *out-of-school time*, which does not reach significance in either model. This simply means we aren't confident that it is associated with *length of residency* or *negative move-outs*. There are many other benefits that could be associated with *out-of-school time*, which are more appropriately assessed directly with child assessments.

The other service area with a different result is *housing stability services*. These are associated with less risk of a general move-out, but more risk of a negative move-out! What could explain this? There is a special Resident Service in this category called *eviction prevention coaching*, which is specifically for households that may have received lease violations and are effectively on a path toward eviction. Households participating in this category are necessarily going to be more closely affiliated with negative move-outs, as it is often a goal to ensure all households receive this type of service before an eviction. In a sub-analysis, not shown here, among all households that ultimately did experience a negative move-out, housing stability services were significantly associated with seven months longer median residency.

What Does This All Mean?

Accounting for differences between regions, populations, properties, and other service participation, we still see that households which participated in community participation, cross-cutting services, financial stability, health and wellness, or housing stability services had significantly longer residencies and less risk of a negative move-out.

Limitations

While we made best efforts to select data in a manner appropriate to this analysis technique, there are some assumptions that would need further review and more sophisticated approaches could be used. For instance, a different type of modeling, called 'parametric survival modeling' or 'accelerated time to failure modeling,' may be appropriate given that the hazard between our service groups are not entirely proportional over time. Further, more variables could be incorporated, such as household demographics, the sub-types of Resident Services rendered, as well as amount of service participation and its change over time. This introduces substantial complexities to the analysis and its interpretation. The present approach was an attempt to keep the analysis as simple and accessible as possible, while still applying as much rigor to the technique, data selection, and adjustments as possible.

Summary

This analysis used an intentional dataset of 9,755 residencies at 73 properties in five regions, for two resident population types, utilizing historically informed criteria to ensure over 85% of *negative move-outs* for the data selection would be observed. This data was also filtered such that properties with enough *observed negative move-outs* were included, senior properties were excluded, and move-outs occurred during confirmed Resident Services availability at each property. These criteria were to promote a fair and unbiased comparison of service participation groups, often making it more difficult to find a positive association with Resident Services. Looking at *move-outs* generally (52% less hazard) or at *negative move-outs* specifically (41% less hazard), Resident Services participation was associated with *longer residencies* and fewer *negative move-outs*, even after removing the influence of region, population served, and the property.

Ultimately, this is an encouraging finding showing Resident Services participants have better housing stability across several types of analyses and across most priority program areas.

Appendix

Survival Analysis Concepts

Left Truncation

Left truncation introduces complexities that are difficult to address. In the speeding ticket example previously mentioned in the introduction, we would probably want to start at the point people get their driver's license. If we simply use a random sample of current drivers, there would be a lot we don't know about them before the start of our analysis, such as if they had ever gotten a ticket before, how many years' experience they have, but we would be missing drivers who had their licenses suspended because of speeding tickets! Not including them in our study would be inaccurate. These types of data issues are called 'left-truncation' meaning they involve issues before the start of our analysis and may have removed observations of interest from our sample. This is also the origin of a common phrase, 'survivorship bias', meaning those who make it into the study 'survived' and are therefore already different than the general population (e.g., they have not gone to jail for speeding). **In our current scenario of housing stability, this means we cannot simply analyze all current residents at a particular period.** Instead we need to look at all the residencies of a sample of move-ins until their move-out or for a set observation window. Otherwise, we would include existing residents with new residents in a way that would skew our analysis. By design, the data we analyzed did not have any left truncation (e.g., all residencies were including starting at their move-in to Mercy Housing).

Right Censoring

Another thing to be aware of is something called 'right censoring,' which simply means that the study never **observed** a person or household experience the event before the end of the study. They never got a speeding ticket. This might not be so bad if all these individuals made it all the way through the end of the study, that would be convenient but is rarely the case. People move away after two years, but the study is three years long. People decide to sell their car and take the bus, etc. They didn't get a speeding ticket, but we don't know if they would have or did later unbeknownst to us in a different city. Fortunately, this type of data is quite common and can be readily handled automatically in our analysis. When we looked into the specific scenario of negative move-outs, we took into account people who had normal move-outs to ensure they were included in the study sample, but also that we appropriately remove them over time. (If it helps, you can think of them counting in the 'denominator' until they move-out, but not in the 'numerator' of negative move-outs.)

References

This analysis was performed in R and made free use of the following packages in this analysis.

Bache, Stefan Milton, and Hadley Wickham. 2014. *Magrittr: A Forward-Pipe Operator for R*. https://CRAN.R-project.org/package=magrittr.

Barrett, Tyson S., Emily Brignone, and Daniel J. Laxman. 2019. *Furniture: Furniture for Quantitative Scientists*. https://CRAN.R-project.org/package=furniture.

Harrison, Ewen, Tom Drake, and Riinu Ots. 2019. *Finalfit: Quickly Create Elegant Regression Results Tables and Plots When Modelling*. https://CRAN.R-project.org/package=finalfit.

Henry, Lionel, and Hadley Wickham. 2019. *Purrr: Functional Programming Tools*. https://CRAN.R-project.org/package=purrr.

Kassambara, Alboukadel. 2018. *Ggpubr: 'Ggplot2' Based Publication Ready Plots*. https://CRAN.R-project.org/package=ggpubr.

Kassambara, Alboukadel, and Marcin Kosinski. 2018. *Survminer: Drawing Survival Curves Using 'Ggplot2'*. https://CRAN.R-project.org/package=survminer.

Müller, Kirill, and Hadley Wickham. 2019. *Tibble: Simple Data Frames*. https://CRAN.R-project.org/package=tibble.

R Core Team. 2019. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Robinson, David, and Alex Hayes. 2019. *Broom: Convert Statistical Analysis Objects into Tidy Tibbles*. https://CRAN.R-project.org/package=broom.

Spinu, Vitalie, Garrett Grolemund, and Hadley Wickham. 2018. *Lubridate: Make Dealing with Dates a Little Easier*. https://CRAN.R-project.org/package=lubridate.

Therneau, Terry M. 2019. *Survival: Survival Analysis*. https://CRAN.R-project.org/package=survival.

Wickham, Hadley. 2017. *Tidyverse: Easily Install and Load the 'Tidyverse'*. https://CRAN.R-project.org/package=tidyverse.

———. 2018. *Scales: Scale Functions for Visualization*. https://CRAN.R-project.org/package=scales.

———. 2019a. *Conflicted: An Alternative Conflict Resolution Strategy*. https://CRAN.R-project.org/package=conflicted.

———. 2019b. *Forcats: Tools for Working with Categorical Variables (Factors)*. https://CRAN.R-project.org/package=forcats.

———. 2019c. *Stringr: Simple, Consistent Wrappers for Common String Operations*. https://CRAN.R-project.org/package=stringr.

Wickham, Hadley, Winston Chang, Lionel Henry, Thomas Lin Pedersen, Kohske Takahashi, Claus Wilke, and Kara Woo. 2019. *Ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics*. https://CRAN.R-project.org/package=ggplot2.

Wickham, Hadley, Romain François, Lionel Henry, and Kirill Müller. 2019. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, and Lionel Henry. 2019. *Tidyr: Easily Tidy Data with 'Spread()' and 'Gather()' Functions*. https://CRAN.R-project.org/package=tidyr.

Wickham, Hadley, Jim Hester, and Romain Francois. 2018. *Readr: Read Rectangular Text Data*. https://CRAN.R-project.org/package=readr.

Xie, Yihui. 2019. *Knitr: A General-Purpose Package for Dynamic Report Generation in R*. https://CRAN.R-project.org/package=knitr.

Zhu, Hao. 2019. *KableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.