Applying Performance Management Tools to Understand and Improve Rapid Re-Housing Program Outcomes

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Abstract

This paper examines the potential for improvement in the performance of Rapid Re-Housing programs in terms of moving people experiencing homelessness quickly and effectively into stable housing. These programs have grown rapidly since their introduction in 2009 and have been evaluated extensively. These evaluations have had mixed results but have generally supported the conclusion that this intervention is equally effective and less expensive than transitional housing programs. Although this literature has clarified the overall effectiveness of this intervention, it provides less insight to local policymakers and program managers on whether their programs are performing as well as possible and what could be done to improve housing outcomes. This analysis employs the tools of performance management—including benchmarking, control charts, process mapping, and performance comparisons across time and providers—to analyze data from the Continuum of Care in Sacramento, California. These tools search for performance outliers that cannot be explained by the underlying variation in the data and then seek to identify the root causes of these deviations. The analysis does find that significant performance deficits have arisen over time and between program providers. If managers could reduce just one-half of the identified performance deficits, the system-level rate of moving clients to stable housing would increase by one-third, a much larger improvement than could be achieved by reasonable budgetary increases.

What are the prospects for improving the performance of Rapid Re-Housing (RRH) programs through the application of performance management analytics? To date, researchers have conducted multiple evaluations of the program (Brown et al., 2017; Byrne et al., 2016; Finkel et al., 2016; Gubits et al., 2018; Rodriguez and Eidelman, 2017). These summative evaluations seek to identify the impact of the intervention as it is operating during the assessment stage of the policy cycle. The results of this work have been mixed. The most rigorous analysis did not find statistically significant program effects, although it found that the costs of RRH were less than usual care (Gubits et al., 2018). Several observational studies have found more positive results, but none have a randomized control group to assess program impacts (Byrne et al., 2016; Finkel et al., 2016; Rodriguez and Eidelman, 2017; Spellman et al., 2014). In sum, the rapid growth of RRH programs has been primarily propelled by the evidence that it is less expensive than shelter care or transitional housing, although the existing evidence has not established it as more effective than other programs.

This article focuses on a related though distinct question: is there room to *improve current outcomes*? These questions are the focus of formative evaluations or performance management processes during the implementation stages of the policy cycle (McDavid, Huse, and Hawthorn, 2018; Scriven, 1991). Specifically, it examines whether there are variations in the outcomes between RRH program providers or over time that indicate the possible presence of performance deficits that, if addressed, could improve system outcomes. This question is important and timely given that the program remains relatively new and has grown dramatically. At the national level, the program model has been in operation only since 2010. Since then, the total number of beds has almost quintupled from 19,842 to 112,961 in 2019, and RRH now constitutes more than 12 percent of the stock of beds devoted to addressing homelessness. The program is delivered in a highly flexible manner wherein most programs apply a progressive engagement model that caters types and amounts of services provided to each client according to their perceived needs (Dunton and Brown, 2019; Shinn and Khadduri, 2020). This level of administrative discretion can promote program efficiency by only providing a minimal amount of support to resolve a client's homelessness, but it also risks producing unmanaged variation that can undermine program effectiveness. Finally, the recent housing market boom has raised questions on whether and how this model can operate effectively in tight housing markets (Batko, Gillespie, and Gold, 2019).

This article examines the prospects for improvement by applying the tools of performance management to RRH data from the Continuum of Care (CoC) in Sacramento, California (Behn, 2014; Cole, 2011; Hatry, 2006). These tools include benchmarking against performance goals, control charts, comparisons across subunits and over time, and process mapping. The goal throughout is to identify anomalies in output and outcome measures that cannot be explained by random variation in the underlying data. When anomalies are identified then the analysis seeks to identify their root causes, thereby highlighting performance issues that require management attention. The analysis identifies significant performance deficits and calculates that addressing the identified problems could increase the number of clients successfully rehoused by RRH programs by 30 to 40 percent.

The article proceeds as follows. The next section describes RRH programs and reviews the existing evaluations of the program. It continues to describe performance management and its application to RRH. The next section describes the data that comes from the Homeless Management Information System (HMIS) in Sacramento, California. The main analytic section begins with a comparison of Sacramento to national performance benchmarks and finds that Sacramento does not meet these benchmarks. The section then continues to diagnose the root causes of the failure to meet these benchmarks. Throughout, the analysis emphasizes the graphical display of data that facilitates communicating results to a wider audience. The conclusion contrasts the results to previous work and provides policy recommendations.

Rapid Re-Housing and Performance Management

RRH is an outgrowth of the housing first movement (Mackie, Johnsen, and Wood, 2017). Traditionally, homeless individuals were moved through a progression of programs, including emergency shelters and transitional housing, in the belief that these programs were necessary before clients could be capable of living independently. Housing First, in contrast, seeks to provide permanent housing as quickly as possible while providing supportive services for substance abuse, employment, and other issues before, during, and after the client is housed.

The RRH approach has been adopted by a range of funders. It was introduced at the national level in 2009 when the American Recovery and Reinvestment Act created the Homelessness Prevention and Re-Housing Program (HPRP). Since then, it has been incorporated into funding by the U.S. Department Veterans Affairs' (VA's) Supportive Services for Veteran Families program and in the U.S. Department of Housing and Urban Development's (HUD's) CoC and Emergency Solutions grant programs. Further funding has been made available from state programs such as the 2018 Homeless Emergency Aid Program in California.

The specific program requirements vary between programs, but they share a common approach—to place clients into housing as quickly as possible. The program provides short-term rental subsidies for periods ranging between a few months up to 2 years. During enrollment, programs provide a range of social services that helps clients find housing and prepares them to independently maintain housing after program completion. Because RRH seeks to help clients who are capable of living independently, but who do need short-term assistance, it has been targeted to those with a middle range of needs.

The programs are designed to be flexible, incorporating a progressive engagement approach that seeks to provide just enough supports to enable the client to succeed. Consequently, caseworkers maintain discretion concerning the types of social services provided (such as substance abuse treatment, employment services, housing search services) and the amounts of financial support provided (such as relief from debts, security deposits, and the amount and length of housing subsidies).

Evaluations of RRH Programs. A sizable literature has evaluated RRH programs. This work has sought to isolate the effects of RRH programs in comparison to alternative treatments that include usual treatment entailing stays in emergency shelters in combination with other available benefits or enrollment in transitional housing programs or receiving long-term housing subsidies (Brown et al., 2017; Burt et al., 2016; Byrne et al., 2014; Cunningham and Batko, 2018; Finkel et al., 2016; Gubits et al., 2018; Mackie, Johnsen, and Wood, 2017; Rodriguez and Eidelman, 2017; Spellman et al., 2014). The results of this work, however, remain inconclusive. The most rigorous random control trial of the intervention did not find statistically significant program effects compared to usual care in terms of housing status and family welfare (Gubits et al., 2018). The point estimates of the study found that RRH achieved better housing outcomes compared to usual care, but the standard errors were too large to draw strong conclusions. This result is due in part to the fact that the study employed an intent-to-treat design and was affected by a significant crossover between treatment groups. For example, 22 percent of the families assigned to the usual care group accessed

RRH services, and only 58 percent of the RRH group enrolled in the program. These factors combined to decrease the statistical power of the trial (Evans, Philips, and Ruffini, 2019).

In an observational study, Rodriguez and Eidelman (2017) employed propensity score matching to compare RRH clients to those served by shelter or transitional housing programs. They found that RRH was more effective than shelters at preventing returns to homelessness, but that RRH was no more effective than transitional housing. Other descriptive studies have found that the program operated as intended. Enrollees who made use of RRH were housed more rapidly than those who do not, and a high proportion of clients achieved housing independence and remained stably housed after program completion (Cunningham and Batko, 2018). More importantly, this work has found that RRH produces similar outcomes compared to traditional transitional housing programs but at a lower cost (Gubits et al., 2018; Rodriguez and Eidelman, 2017).

Two main caveats attach to this work. First, it examines the early stages of program performance, using data primarily prior to 2014 when the national housing market was still recovering from the Great Recession. Early evidence did find that the program achieved higher levels of success in communities with higher apartment vacancy rates (Spellman et al., 2014). Second, these early programs often screened their clients, focusing on families with children who could meet certain income minimums. Thus, it is less certain whether these results may be attained for broader subpopulations and in high-cost housing markets.

Although these studies were not focused on improving program performance, they did highlight several potential avenues for doing so. Rodriguez and Eidelman (2017) found that there is significant variation between programs in terms of returns to homelessness, suggesting that some programs could be improved. The findings concerning the effects of program characteristics are mixed. Some found that program features did not correlate with outcomes (Finkel et al., 2016), though others found weak evidence that increasing household income did improve success rates (Brown et al., 2017). Overall, these authors conclude that there is a need for additional study that examines the impacts of specific program features.

Performance Management and RRH. In addition to efforts to determine the effectiveness of RRH programs, there have been calls to apply performance management to maintain and improve program performance (Cepiku, 2017; NAEH, 2016; Turner, 2015). Performance management practices come in a variety of modalities, each with its own nomenclature, including PerformanceStat, Compstat, managing for results, lean/six sigma, to name just a few. This management strategy incorporates several key elements (Behn, 2014; Cole, 2011). It identifies a series of performance metrics of an organization's processes, outputs, and outcomes that are tied to the organization's strategic objectives. It analyzes these metrics to highlight anomalies that may be associated with performance deficits or performance exemplars. Then, managers conduct regular meetings to review analyses of the metrics and to develop and followup on strategies to improve the program's effectiveness based on these data.

Performance management complements evaluation studies. Evaluations tend to be conducted at the assessment stage of the program cycle after a program has been in operation sufficiently long to generate its intended effects. Evaluators come from outside of management structures, either in a specialized research office or outside consultants. These studies emphasize research designs that control for confounding factors that may influence observed program outcomes and, thus, require significant resources and time to complete.

Performance management relies on the evaluation framework to identify metrics that are valid performance indicators, but its objectives and the manner in which it is conducted differ. Performance management is conducted close to program managers and provides ongoing feedback rather than one-time assessments. It focuses less attention on controlling confounding factors and devotes more attention to finding actionable information. Experimentation with management strategies and rapid feedback on results substitute for more rigorous research designs. This learning-by-doing strategy is not immune to inferential errors that more rigorous evaluations seek to filter out, but it does provide opportunities to correct issues with program operations in real-time.

The application of performance management in the public and nonprofit sectors has been widely touted (Behn, 2014; Forsythe, 2001; Osborne and Gaebler, 1992). These advocates argue that greater attention to output and outcome metrics in public sector management keeps public agencies focused on key goals. Furthermore, performance management permits greater managerial discretion to find methods for achieving those goals while maintaining accountability through transparent metrics. There is little doubt that data-driven management has had a profound impact on private sector firms (Womack, Jones, and Roos, 2007).

There have been notable successes with performance management in the public and nonprofit sectors where agencies have improved the quality and availability of services and strengthened management practices (Lee, McGuire, and Kim, 2018; Poister, Pasha, and Edwards, 2013; Walker, Damanpour, and Devece, 2011). CompStat, a performance management system developed for policing in New York City, is credited with helping reduce crime in that city and has been widely replicated (Behn 2014; Bratton and Malinowski, 2008; Smith and Bratton, 2001; Willis, Weisburd, and Mastrofski, 2003). HUD developed and operated its own performance management system called HUDStat beginning in 2011, and it employed its continuous review of data to tackle veteran homelessness (HUD PD&R, 2012). Also, Culhane et al. (2008) reported on two local initiatives in Arizona and Columbus, Ohio, that developed metrics and employed them to strive toward system-level performance goals.

Nevertheless, the record of successful application of performance management in the public and nonprofit sectors has been spotty at best (Moynihan, 2008; Radin, 2006). For example, Sanger (2013) examined 190 cities that published performance metrics online and found that only 27 cities (14 percent) applied best practices to their use of metrics. Also, after a change in administrations in Washington, D.C., HUDStat was discontinued in 2016.

A number of factors make it difficult to maintain performance management regimes. Public agencies and nonprofits are typically staffed by line workers who are experts in program administration but lack analytic training to manage and analyze data. They also often lack modern data processing capabilities that restrict the range and quality of metrics that may be brought to bear in managerial decisionmaking. The rise of HMIS systems has improved this situation greatly, though many communities continue to be challenged by low data quality and participation levels in their HMIS. Finally, budgetary and time constraints often conspire to force managers to focus on short-run fixes rather than long-run program improvements (Behn, 2013).

Despite these constraints, homelessness policy and RRH programs, in particular, constitute a policy area that demonstrates some promise for escaping this web of impediments. The main goals of the program—helping people back into stable housing—receives wide support, allowing for greater emphasis on outcome measures. High-quality data is becoming increasingly available due to the rise of homeless management information systems promoted by HUD. The structure of programs with services provided by multiple agencies provides an excellent basis for performance comparisons. In addition, the flexibility, which is a hallmark of the program, offers extensive potential for experimentation with different packages of services directed at specific subpopulations.

Based on these prospects, the practitioner community has published guides on how to use available data to monitor and approve programs. Canada has published a performance management guide that provides a high-level overview of the analytic approach (Turner, 2015). The National Alliance to End Homeless (NAEH), in coordination with the U.S. Interagency Council on Homelessness (USICH), HUD, and VA, has promulgated benchmarks for three key performance metrics: (1) days homeless prior to attaining housing (average days homeless), (2) percent of clients that exit to permanent housing situations (successful exits), and (3) percent of clients that return to homelessness within a year after a successful exit (returns) (NAEH, 2016). Based on stakeholder consultations, NAEH put forth the following system goals:

1. On average, clients should take 30 days or less to move into permanent placements after program enrollment.

2. Eighty percent of clients should exit to permanent placements.

3. No more than 15 percent of clients who exit to permanent placements should become homeless again within a year.

The report then details program core competencies in the areas of housing identification, rental assistance, and case management that would enable CoCs to achieve these performance benchmarks.

Building on these benchmarks, HUD has recently introduced a strategy and analysis toolkit called Stella that presents CoC data in a manner that permits analysis of these metrics. The dashboards are based on longitudinal system analysis data that each CoC will upload each year. It provides overviews on the three NAEH performance metrics and allows users to analyze performance by client subgroups and by pathways, combinations of programs employed by clients. In particular, the system points out specific pathways and user groups that are impacting performance to point managers to important problems. A second analytic toolkit that is intended to facilitate resource planning is in development.

The analysis in this paper seeks to facilitate the diffusion of performance management by homeless policymakers and administrators by demonstrating the analytic strategies that can be applied to highlight performance issues and illustrating the scope of the performance improvement that can be achieved by acting on these insights.

Data

The data for this study comprises a comprehensive, de-identified dataset from the Sacramento CoC HMIS provided to the researcher by Sacramento County. All the metrics employed in the analysis are taken directly from HMIS or are calculations using HMIS data fields.[1] The analysis focuses on 4,839 program enrollments between 2015 and 2018. Pre-2015 RRH enrollments are excluded due to concerns with data quality, although these earlier data are used to record clients' previous experience in emergency shelter and street outreach programs. The data runs through May 2019 for the purposes of tracking returns to homelessness. Thus, only clients who exit an RRH program into stable housing prior to May 2018 are included in the calculations for returns to homelessness within 1 year. Within these enrollments, 516 households enrolled in the RRH program more than once during these 4 years, leaving the number of distinct households at 4,268.

The demographic characteristics of the heads of households served by Sacramento RRH programs are shown in exhibit 1. This group is similar to the populations analyzed by previous work on RRH based on HMIS data from Indianapolis, Indiana, and the state of Georgia (Brown et al., 2017; Rodriguez and Eidelman, 2017). The average age and the percent of male clients fall between the percentage from the other two studies. In terms of race and ethnicity, the proportion of White clients is similar, although the proportion of African-Americans is lower while the proportion of Latinos is higher in Sacramento, reflecting the different ethnic composition of California. Compared with the Georgia sample, the proportion of households who enroll in Sacramento RRH with no income (9.8 percent versus 21.7 percent) and who have children (57.5 percent versus 65.4 percent) are comparable.

There are relevant differences in the Sacramento population. The percent of enrollees with disabilities is much higher in Sacramento, 47.0 percent compared to 15.1 percent in Georgia and 24.2 percent in the Indianapolis study, although it is uncertain whether these differences are due to data entry practices or real differences in population characteristics. Sacramento clients are less likely to have had previous emergency shelter stay, 14.6 percent compared to 23.5 percent in Georgia. One striking difference between these Sacramento data and the data from Indianapolis and Georgia is that Sacramento's rental market is significantly tighter, during the study period. From 2017 to the present, Sacramento rents based on the Zillow Rent Index have increased over 40 percent, the third-highest rate of increase among the 50 largest metropolitan areas.

[1] There are instances in which calculations yielded anomalous results, most likely due to data entry errors. For example, the days spent homeless prior to housing sometimes yielded negative results, probably due to a coding error for the date client moved into housing. Similarly, observations for some program enrollments lacked a housing move-in date, but the client then exited to permanent housing after a year or more in the program. These records are probably due to missing move-in dates. In both of these cases, the variables were coded as missing.

Exhibit 1

Demographic Characteristics of Head of Household

Demographic Variables	Sacramento (n=4268)	Georgia State (n=379)	Indianapolis (n=203)
Age	40.3	37.1	45.1
Male (%)	41.0	25.9	62.6
White (%)	29.8	23.5	28.0
African-American (%)	48.6	73.1	67.9
Latino (%)	13.8	3.4	n/a
No Cash Income Source at Enrollment (%)	9.8	21.7	n/a
Total Household Income	1,067.9	n/a	578.1
Households with Children (%)	57.5	65.4	n/a
Veteran (%)	29.9	4.8	15.8
Disabled (%)	47.0	15.1	24.2
Previous Shelter Stay (%)	14.6	23.5	n/a

N/A = data not available.

Analysis

The performance management paradigm broadly seeks to identify anomalies in program performance that cannot be explained by the natural variation in metrics. It then focuses on the negative anomalies to find problems that may need to be addressed and on the positive anomalies that may provide clues on how to improve performance. This search for anomalies can take on many forms and search down many paths, but the performance management paradigm offers a rich tool kit of methods, borrowing extensively from descriptive, exploratory, and inferential statistics, for presenting and analyzing data. Once anomalies are identified, managers are then guided to investigate likely reasons for the anomalies through root cause analysis and other analytic heuristics and to develop and test improvement strategies based on the root causes of identified issues (Cole, 2011).

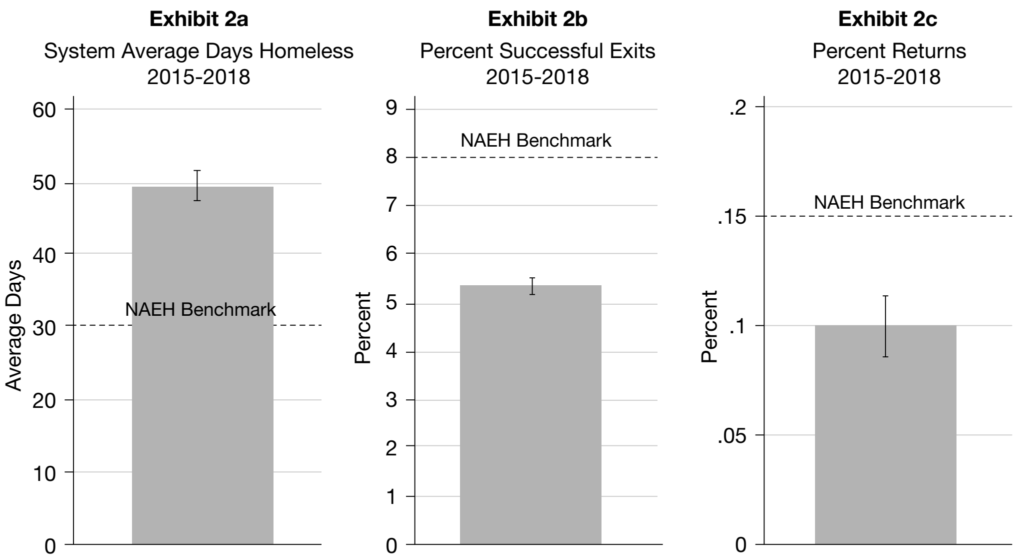
This article focuses on a subset of performance management's analytic tool kit that is most commonly employed. It begins with benchmarking, the comparison of performance metrics with standards that have either been established externally or internally through strategic planning. It then turns to the use of control charts, a common technique that examines performance variations over time to assess whether a process is controlled, in a statistical sense, or not. It then continues the search for anomalies by expanding these comparisons across time and between subunits (for example, program providers), two of the most common comparisons employed in performance management (Behn, 2014). Then the analysis introduces process mapping, which tracks the steps through which clients proceed when enrolled in an RRH program. Once these steps are identified, metrics to evaluate the performance of each step are identified to analyze the entire program process. Based on these performance analyses, estimates of potential performance improvement are developed based on the reasonable corrections that can be made to program performance.

The analysis begins with benchmarking Sacramento's performance with the standards set forth by NAEH. These comparisons are based on all program enrollments that began on or after January 1, 2015, and ended before May 30, 2018. Later exits are excluded to ensure that all records have a full year's worth of data to track returns to homelessness. The results are presented in exhibit 2.

The dashed lines in each graph represent the NAEH benchmark targets, and the whiskers on the top of each bar represent the 95 percent confidence interval for the sample mean or proportion. Sacramento only meets one of these three benchmarks, "returns to homelessness." The average time to housing of almost 50 days is nearly 66 percent longer than the 30-day benchmark, and the percent of clients that exit to permanent housing placements is less than 55 percent, far below the 80 percent benchmark. The percentage of returns to homelessness, on the other hand, is below the benchmark of 15 percent.

Exhibits 2a–c

Comparisons to National Alliance to End Homelessness Benchmarks



NAEH = National Alliance to End Homelessness.

These results are cause for concern. Although most clients who exit into permanent placements appear to remain stably housed, Sacramento's system takes a longer than expected time to find permanent housing for RRH clients, and fewer than expected clients are stably housed when they exit the program.

The insights that are drawn from these benchmark comparisons, nevertheless, are limited. As NAEH recognizes, their benchmarks may not be appropriate for all communities. In their review of early results from RRH programs, Shinn and Khadduri (2020) found that many programs did meet these benchmarks or came close. Nevertheless, Sacramento's performance may be the result of particular regional or historical characteristics that hamper the effectiveness of RRH, rather than issues with the system itself. Thus, further investigation of the root causes of these performance deficits is warranted to test the degree to which these deficits can be connected to the operations of Sacramento RRH programs and, if that is the case, to identify areas in which improvement strategies should be targeted.

Control Charts. The next step is to examine the control charts for these three key performance metrics. These charts graph metrics over time and compare them to upper and lower control bounds that are based on the natural variation of outcomes. There are many versions of control charts, but here, we employ basic ones that set the upper and lower control bounds at three standard deviations above and below the mean. The goal of these charts is to provide a clear, visual evaluation of whether a process is under control or whether there are outcomes that are so far outside of the norm (for example, more than three standard deviations from the mean) that they require immediate attention.

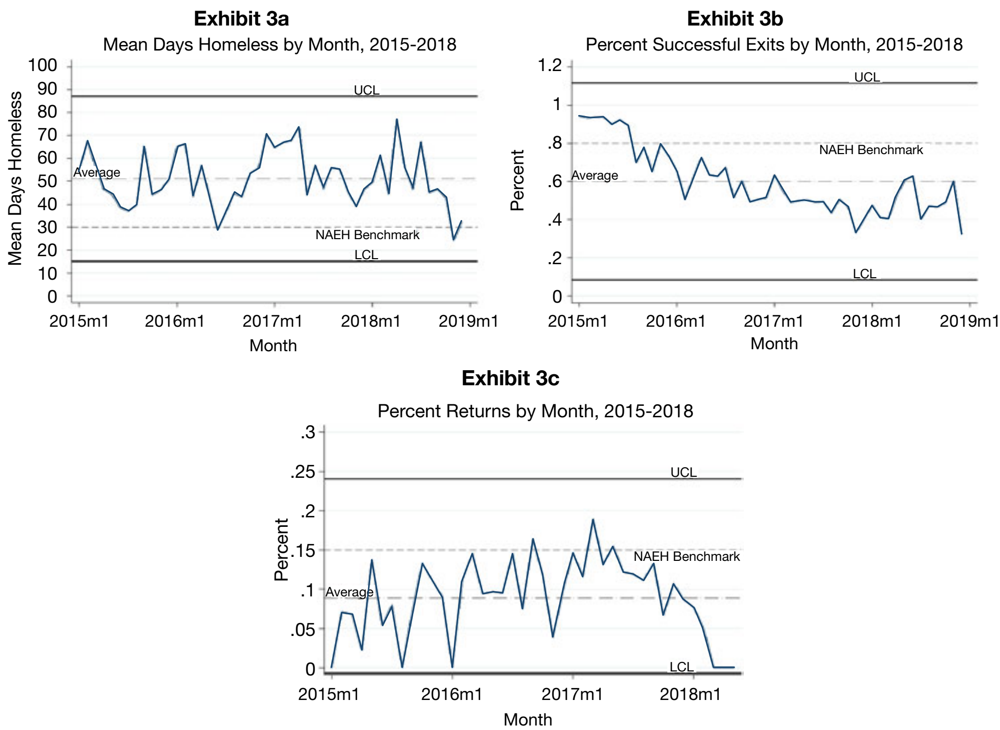
The control charts from the three NAEH metrics are presented in exhibits 3a to 3c. The short-dashed line is the outcome for the cohort of clients entering RRH programs each month. The long-dashed lines with dots are the average outcome, and the thick black lines present the upper and lower control limits.[2] The NAEH benchmark for each metric is shown as a short-dashed line. In all three cases, outcomes are considered stable from a statistical perspective because in no month does the measure cross the upper or lower control limits. Nevertheless, the control charts do reveal problems. For the days in the program prior to being housed, the average number of days is far above the 30-day benchmark, and in only 2 months does the system meet the benchmark. For the percent of clients exiting to stable housing, the system did briefly meet the benchmarks in early 2015, but since then, performance has steadily declined.

The analysis of returns to homelessness is more nuanced. Exhibit 3c indicates that the rate of returns is typically below the NAEH benchmark except for a few months in late 2016 and early 2017. It appears, nevertheless, that the percentage of returns was trending upward until the beginning of 2017 and has since trended down strongly. There are, however, two major caveats that need to be considered. First, the results for April and May of 2018 are based on clients that enrolled RRH in those months and exited by May. These fast exits are biased toward clients that have greater resources that enable them to find stable housing on their own, which makes the lack of any returns less noteworthy. Second, unlike the other two control charts, this one ends in May of 2018 instead of extending throughout the year because of the need for a full year of data to determine whether a return has occurred.

[2] When the lower control limit is negative, it is set just below zero.

Exhibits 3a–c

Control Charts for National Alliance to End Homelessness Benchmarks



m1 = January. NAEH = National Alliance to End Homelessness. UCL = upper control limit. LCL = lower control limit.

Although returns to homelessness remains an important metric and it has been the primary metric employed in evaluations of RRH (Brown et al., 2017; Byrne et al., 2016; Rodriguez and Eidelman, 2017), this feature of the metric limits its usefulness for ongoing program management because it reflects relatively dated program performance. The average length of stay in RRH is about 155 days. Adding that program stay to the 365-day projection required to determine whether a client has returned to homelessness means that this metric is primarily reporting on program performance for clients that enrolled almost a year and one-half prior to the analysis. Any performance issues that the metric may signal may no longer be relevant to current management decisions.

On the other hand, examining the returns metric in conjunction with the successful exit metric demonstrates the value of taking multiple perspectives on program performance. As the successful exit rate declined through 2017, the returns to homelessness also decreased, suggesting that the clients that did find stable housing had a greater capacity to remain housed. Conversely, as a community works to improve their rate of successful permanent housing placements out of RRH, managers would need to check the returns metric to ensure that their efforts to increase successful exits did not lead programs to the exit of clients who were not prepared to maintain housing on their own and therefore were more likely to return to homelessness. In this way, the two metrics work in conjunction to provide checks on such unintended consequences.

Comparisons Over Time. To further investigate the significance of the trends observed in the control charts for successful exits and returns, exhibits 4a and 4b show the average rates for the four cohorts enrolling in RRH in each of the years 2015 to 2018. In these bar charts, the confidence intervals are adjusted such that visual inspection of the overlap between confidence intervals is a valid statistical test (Goldstein and Healy, 1995). When the confidence intervals overlap between 2 years, one cannot reject the null hypothesis at the 5-percent level of significance that there is no difference between the years.[3] A key goal of performance management is to only focus on performance anomalies that cannot be explained by the normal variation in performance, making normal hypothesis testing of group differences essential. Presenting these differences in bar charts with confidence intervals facilitates the communication of these tests to a broader audience.

Exhibit 4a shows clearly that there has been a deterioration in the percentage of clients with successful exits from RRH programs. In 2015, Sacramento met the NAEH benchmark, but the success rate tumbled to 57 percent in 2016 and experienced a further, statistically significant decrease in 2017 and 2018. Returns to homelessness in exhibit 4b provides some additional nuance beyond the control chart. Sacramento achieved the NAEH benchmark in all years, although the rate did increase by a statistically significant amount between 2015 and 2017. The year 2018 saw a large decline but also has a large confidence interval due to the smaller number of exits in 2018. Thus, although the rate in 2018 is statistically significantly lower than 2017, it does not differ from the other years once the margin of error is taken into account. In sum, positive changes may have occurred in 2018 that enabled RRH clients to retain housing, and although the evidence remains weak, further investigation may be warranted.

Exhibits 4a and 4b

National Alliance to End Homelessness Benchmarks by Year

Exhibit 4a

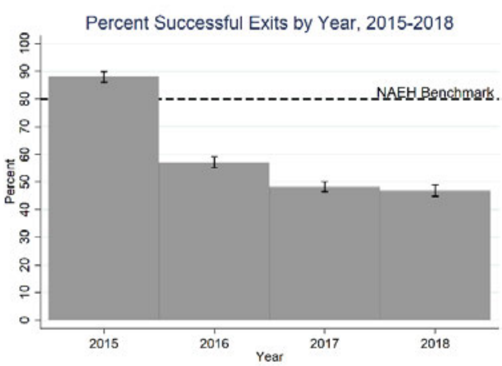
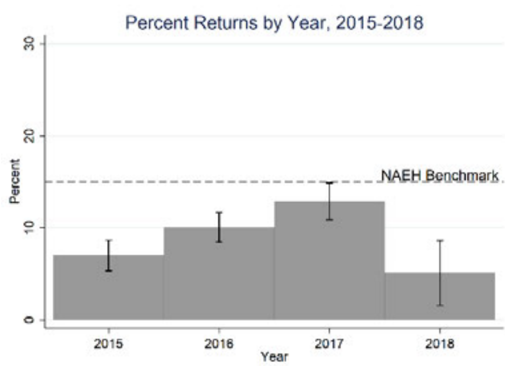


Exhibit 4b



NAEH = National Alliance to End Homelessness.

[3] When comparing just two groups, the confidence intervals can be adjusted exactly to yield accurate hypothesis tests. When a data visualization includes multiple groups, the adjustment is averaged over every pair-wise comparison. Consequently, there are comparisons for which the significance level is slightly higher or lower than 5 percent.

In sum, the performance of RRH is stable in a statistical sense. Nonetheless, in terms of successful exits, the performance has deteriorated in recent years. The next step is to investigate the possible causes of this deterioration.

Program Comparisons. One tactic for investigating the root causes of observed performance deficits is to compare performance across subgroups within a system. RRH programs in Sacramento have been provided by 16 different providers, although not all have been active all years. This analysis focuses on 2017 data from nine programs that have been active in 2015 through 2018 and have served on average at least five clients per year. The comparisons are presented in exhibits 5a–c.

These charts begin to provide more useful clues on where performance improvement efforts should be focused. First, though, it is important to note two caveats that arise as the analysis examines ever more narrowly defined subgroups. First, as seen in the charts in exhibit 5, the estimates of the group means become significantly less precise and have much wider confidence intervals compared to previous graphs. This issue arises because point estimates from smaller samples have larger standard errors. These errors limit the distinctions that can be drawn between subgroups. For example, in exhibit 5a, the average days of homelessness for programs B to I vary widely from 63 to 39 days. Considering the overlaps in confidence intervals though, the average performance of programs B through G cannot be distinguished because of the large standard errors in the estimates. Similarly, programs E through I cannot be distinguished. Second, as the number of subgroup comparisons in the analysis increases, the probability of incorrectly identifying performance differences where none exists (for example, Type I errors) increases dramatically (Ioannidis, 2005). This multiple testing problem is well understood in evaluation research (Miller, 2012), although it does not feature prominently in the performance management literature.

Acknowledging these limitations, exhibit 5a provides two potentially important insights about days to housing. First, no program meets the NAEH standard of 30 days of homelessness prior to moving into housing, with most hovering between 45 and 55 days. This consistent level of performance indicates that managers may face challenges in efforts to achieve NAEH benchmarks. There are no existing examples of strong performance over time or across programs that could provide a model method by which the system could identify housing and move clients more quickly. Rather, managers will have to develop and implement wholly new strategies to address this problem.

Exhibits 5a–c

Comparisons of Program Performance, 2017

Exhibit 5a

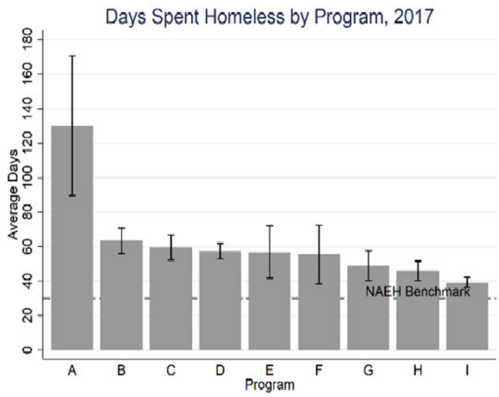


Exhibit 5b

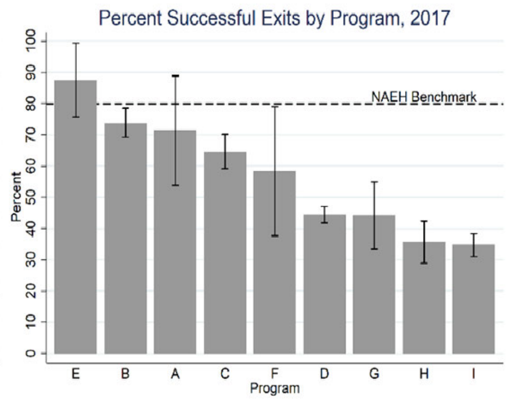
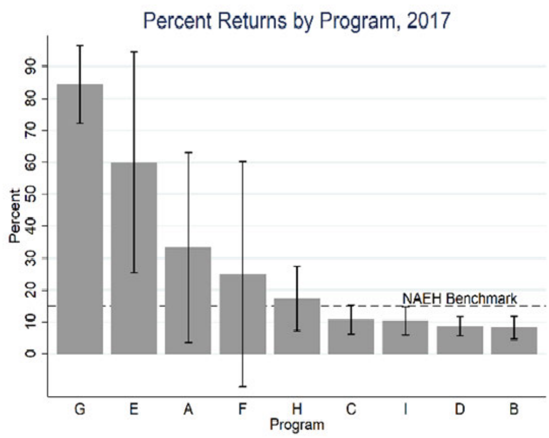


Exhibit 5c



NAEH = National Alliance to End Homelessness.

Second, the data do point out a possible problem in program A. Clients in that program take a significantly longer amount of time to find housing, over 130 days on average, and the fact that the confidence interval does not overlap with any other confidence intervals indicates that this level of poor performance cannot be attributed to random variation.

Exhibit 5b demonstrates that there is much great inter-program variation in terms of successful exits. Program performance ranges between 87.5 percent of clients being placed in stable housing to less than 35 percent. Although the width of the confidence intervals indicates that there is much uncertainty with these data, there are stronger and poor performers. Programs E, B, A, and C constitute a group of higher performers, and programs D, G, H, and I are performing less well. It is less certain how well program F is faring in comparison because its confidence interval overlaps both high and low performing programs.

Exhibit 5c shows a similar division of programs between high and low performers in the term of returns to homelessness. Four programs (C, I, D, and B) meet the NAEH benchmark of 15 percent or fewer clients returning to homelessness. Two programs (G and E) have significantly more of their clients who fall back into homelessness, whereas the results for three programs (A, F, H) are too uncertain to determine whether they should be classed with the higher or lower performing programs.

These comparisons begin to reveal potential strategies for performance improvement by distinguishing areas of strong and poor performance. The poor performers, such as program A in terms of length of time spent homeless or program G that combine low rates of successful exits and a high rate of returns, need attention to see if their poor performance can be improved. Program E reports very high rates of successful exits, but also has the second highest rate of returns, which indicates a possible issue that this provider exits its clients too quickly or is overly optimistic concerning the permanence of their placements at the time of exit. Also, programs that are faring better, such as programs B and C that combine relatively high rates of successful exits and low rates of return, can be further examined to determine whether they employ specific strategies that can and should be replicated by lower-performing programs.

Process Mapping. Process mapping is a technique commonly employed in performance management analyses to identify the root causes of high or low performance, and HUD has recommended its application for managing RRH programs (HUD, 2014). It involves mapping out the steps of helping clients within RRH programs and identifying metrics that can be used to assess the performance of each step of the process. The goal is to identify whether any specific steps are leading to overall problems and to determine whether the process is working well as a whole. Specifically, given the analysis that shows that performance has deteriorated, these metrics can assess which if any steps in this process have functioned more poorly over time.

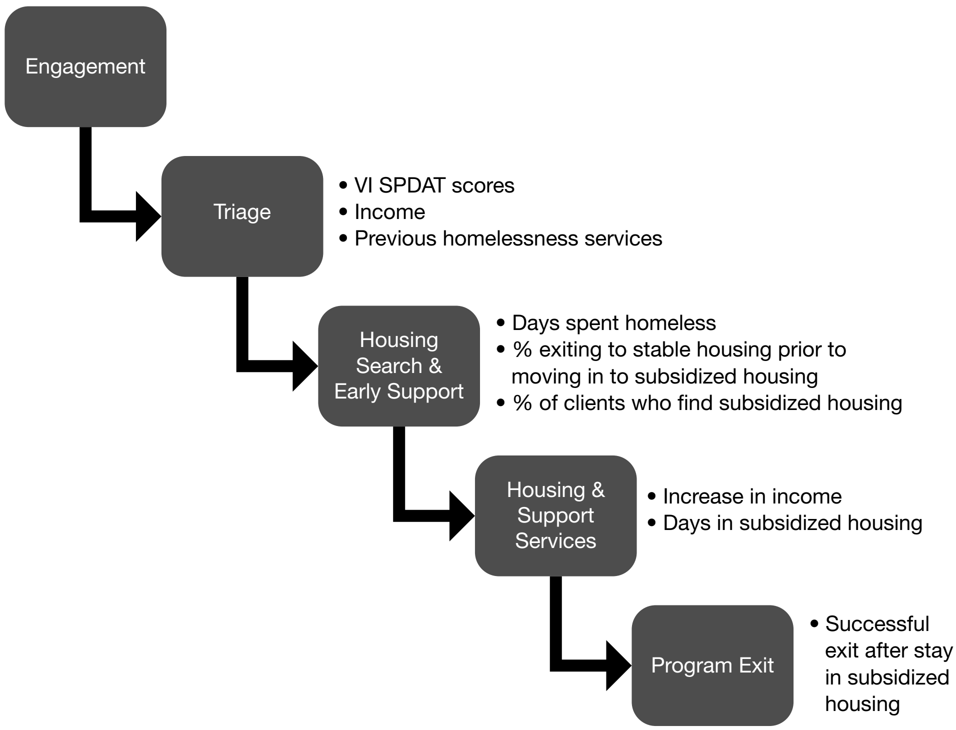
Exhibit 6 presents a basic description of the RRH process.[4] At each step, metrics that can be calculated based on HMIS data are proposed. Other metrics based on HMIS data are possible and, with additional data gathering, a CoC could implement still others.[5] Nevertheless, this list provides a useful first-cut analysis of the process. Clients begin the RRH program by first engaging in the homelessness crisis system. Then there is a triage process by which clients that are well suited to benefit from RRH are referred to an RRH provider. Once clients are enrolled in RRH, they are provided with a range of services. Caseworkers may engage in diversion practices that seek to identify solutions to a client's homelessness that does not require a stay in subsidized rental housing. They are also offered help with housing identification and leasing and other social services. Once they identify and occupy a subsidized housing unit, social services continue to strengthen the client's ability to live independently after the program is completed. Finally, clients are exited from the program.

[4] Sacramento has not fully implemented a centralized coordinated entry system. Thus, not all RRH clients enter the program in the same manner. Some are referred directly into RRH, whereas others may be referred to RRH through emergency shelters or street outreach caseworkers. These steps still provide a rough guide to the process.

[5] Often, process mapping analyzes the time required for each step in the process to identify bottlenecks. In a system with a fully developed coordinated entry system, such time markers can be collected with the dates of evaluation and of referral actions. Unfortunately, these data do not have these timestamps.

Exhibit 6

Process Map and Relevant Metrics



VI-SPDAT = vulnerability index–service prioritization decision tool.

For the triage stage, the metrics examine whether appropriate clients are being sent to the RRH program. RRH is a short-term program that assumes that clients will be able to remain housed independently at the end of the program. Thus, it targets clients that have no more than a medium level of vulnerabilities and demonstrate the capacity to earn enough to afford housing in the long run. Three metrics are available. The first is the client's VI-SPDAT score (Vulnerability Index–Service Prioritization Decision Tool), which is a commonly used instrument to rate the health, medical, and social vulnerabilities of clients. The scores range between 0 and 20, with higher scores indicating a higher level of need. There are slightly different instruments for transition-aged youth and families. Thus, all scores are standardized to make them comparable. The second is an indicator of whether the household had any income at the time of enrollment. The third is whether the client had previously been enrolled in an emergency shelter or street outreach. Previous bouts of homelessness may indicate that the client is more vulnerable, and previous research has shown that previous episodes increase the risk of a return to homelessness (Byrne et al., 2016; Rodriguez and Eidelman, 2017). The metric employed here counts any previous enrollment in an emergency shelter or street outreach as experience with homelessness. This specific metric differs from Rodriguez and Eidelman (2017) in that it includes street outreach and differs from Byrne et al. (2016) in that it does not include other contacts with the Veterans Administration. Including street outreach enrollments in this metric has a major impact. Exhibit 1 shows that 14.6 percent of RRH clients had a previous shelter stay. In contrast, when one examines both shelter and street outreach enrollments in 2018, almost 80 percent of RRH clients had been previously homeless.

To assess the quality and effectiveness of housing search and early support services, there are three metrics. The first is the number of days until housing is secured. This metric is similar to the NAEH benchmark, although it is restricted to clients who do find subsidized housing. The second is the percentage of clients that exit the program into stable housing before receiving subsidized housing. This metric captures the effectiveness of diversion services that may be provided. The third metric is the percentage of households that find and move into a rental property through their RRH program. Ideally, information on the range of services and the amounts of cash supports provided to each client would be telling. Although these data are recorded, the quality of these data was not sufficient to include them in the analysis.

Once housed, RRH seeks to help the client prepare for life on their own. One goal is to increase their income, and another is to move them to self-sufficiency as rapidly as possible, which is tracked by the length of time spent in subsidized housing. Finally, at the time of exiting the program after receiving the full suite of services, a metric is the percent of clients who exit into stable housing (this percentage only includes clients that have moved into a rental through their RRH program).

To assess whether the deterioration in performance in exits to stable housing may be attributable to specific steps in the program process, we examine the trends of these process metrics over time, examining whether issues have arisen that correlated with the decrease in successful exits. Exhibit 7 presents the changes of metrics in the triage step to check whether the triage process has been referring more difficult to serve clients to RRH. The evidence suggests that that has not changed. Exhibit 7a shows that the average VI-SPDAT scored has changed little over the 4 years, ranging between 7.8 and 8.6 on the 20-point scale. Similarly, exhibit 7b shows that the proportion of clients with no income at the start of the program remained steady at about 10 percent. There was a statistically significant, although small, increase in the proportion of households with no income between 2017 and 2018, but the proportion in 2018 does not differ from earlier years. In contrast, there is an indication in exhibit 7c that the proportion of clients that have previously experienced bouts of homelessness had increased from 2016 to 2018, although the 2018 percent was the same as in 2015 when program performance was stronger. The consistently high percentage of households that have previously experienced homelessness, nevertheless, is possibly a sign of system-level difficulties. Under housing first principles, RRH programs are intended to engage clients early in their experience with homelessness and to provide them housing quickly to avoid the accumulation of problems that arise from homelessness. These data, however, indicate that Sacramento is only engaging clients in RRH after they have struggled with housing instability for a longer period.

Exhibit 8 shows the metrics for pre-move-in services to assess whether there are any problems with the services provided to households early after program enrollment. Two metrics (exhibits 8a and 8b), the number of days until move in and percent housed prior to moving into a rental subsidized by the RRH program, show little change over time and are unlikely to be the root causes of decreased performance. The decrease in the percent housed without RRH subsidies in 2018 is likely due to data truncation caused by the shorter time some of these households have been enrolled. In contrast, the percentage of clients that do find housing after enrolling in RRH has declined sharply over the years, from 78 percent in 2015 to 38 percent in 2017 and 2018. This is an anomaly that requires further investigation.

Exhibits 7a–c

Triage Process Metrics

Exhibit 7a

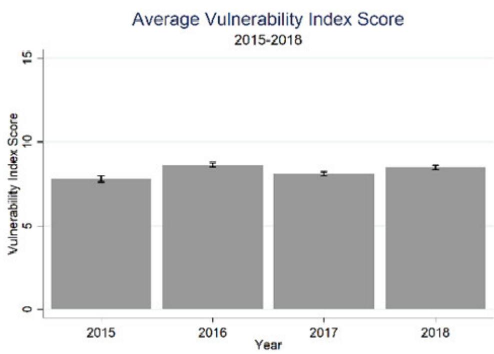


Exhibit 7b

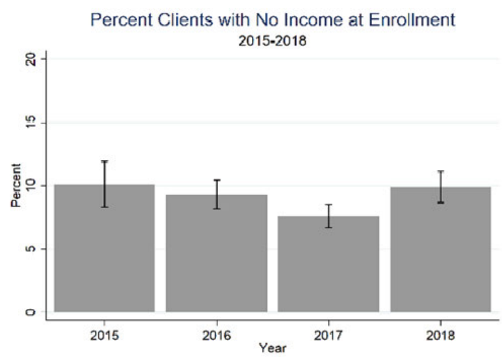
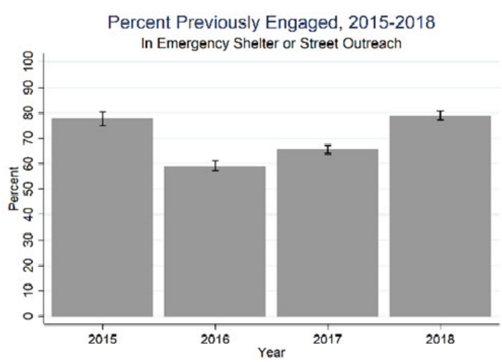


Exhibit 7c



First, though, we examine the metrics for services after the client is placed in housing and upon exit. Exhibit 9a shows that for the subset of clients that do move into subsidized housing, success rates have been steadily at or above 90 percent over time. As seen in exhibit 9b, they have averaged about 180 days in subsidized housing from 2015 through 2017. The much lower number for 2018 is due to data truncation, in which clients that enter later in the year did not have time to complete the program and have their stay recorded in these data. The percentage of clients that increase their income shown in exhibit 9c, in contrast, is another source of concern. The percentage of clients that increased their income during the program dropped from 20 percent in 2015 to less than 8 percent.

Exhibits 8a–c

Early Program Services Metrics

Exhibit 8a

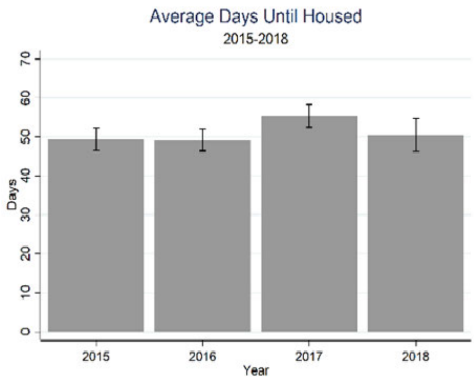


Exhibit 8b

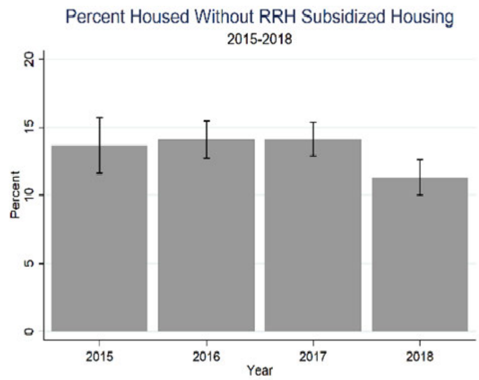
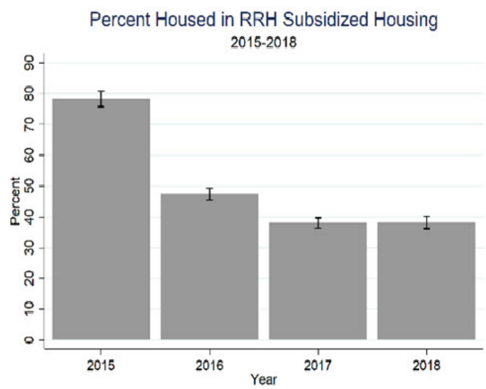


Exhibit 8c



RRH = rapid re-housing.

In sum, the review of the program process pointed out two issues that require attention. The first is that an increasing proportion of clients fail to find a housing option even after they are enrolled in the program, and that the program is not providing sufficient help to clients to enable them to increase their earning potential and afford housing on their own once the program is completed.

To delve deeper into the root causes of these process issues, comparisons between providers over time can be made. Unfortunately, not all providers operated in all years, and some had less than five clients in a year. Thus, exhibit 10 focuses on the five providers with sufficient data (Providers B, C, D, H, and I in previous graphs). Looking at successful move-ins, a clear distinction is seen between three providers (D, H, and I) that have had increasing problems finding housing for their RRH clients compared to two others (B and C) that have consistently performed better than D, H, and I since 2016. In terms of the percent of clients who increase their incomes, a similar pattern emerges. Although all programs are only able to increase the incomes of a minority of their clients, two programs, B and C, sustained higher levels of performance. Program C consistently achieved desired outcomes for between 25 and 30 percent of its clients, and program B steadily improved its performance. In 2018, they both approached or exceeded 15 percent, a benchmark employed by some continuums (Batko, Gillespie, and Gold, 2019). In contrast, programs D, H, and I, as with their performance in finding housing, experienced dramatic and consistent deterioration in the proportion of clients for whom they were able to increase their incomes.

Exhibits 9a–c

Post-Housing Program Services Metrics

Exhibit 9a

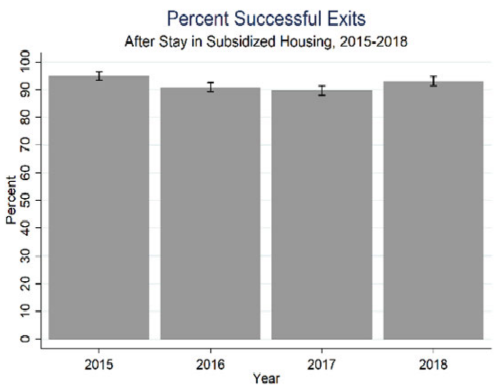


Exhibit 9b

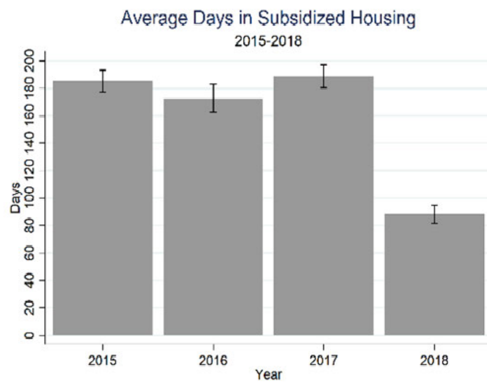
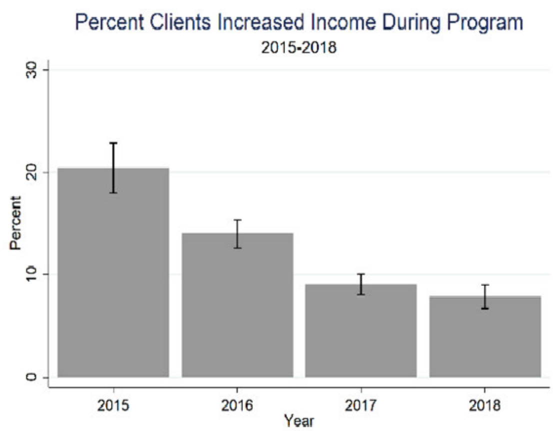


Exhibit 9c



To summarize, the analysis followed a path delineated by the questions raised at each level of inquiry. First, significant performance deficits were identified through comparisons with NAEH benchmarks. The root causes of these deficits were further examined with control charts that indicated that, although the processes were in statistical control, the results for successful exits showed worrisome deterioration in performance over time. To examine the source of this deterioration, comparisons between program providers were made that revealed significant variance in performance. Delving into the causes through process analysis placed further focus on issues related to successfully completing the housing search process and helping clients increase income.

Exhibits 10a and 10b

Outcomes by Program and Year

Exhibit 10a

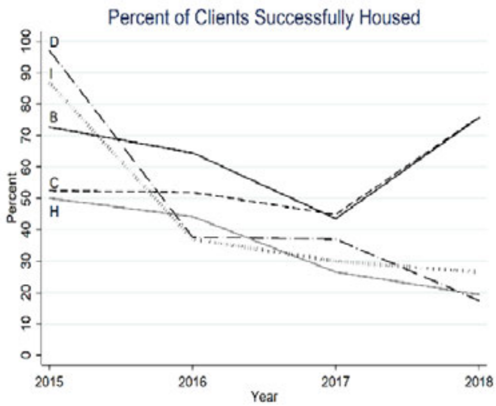
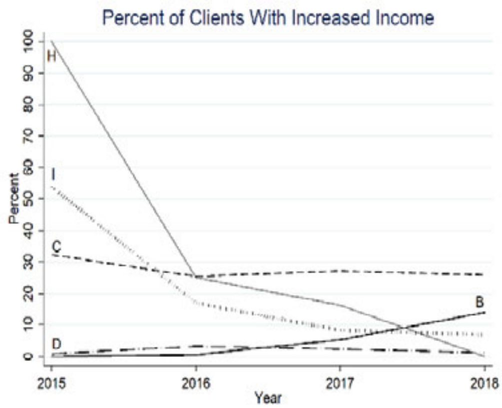


Exhibit 10b



These insights provide useful and actionable insights for program-level and system-level managers. There is room to address issues with finding housing for RRH clients and for program supports that seek to increase clients' capacity to afford housing independently. Moreover, the analysis identifies three programs, D, H, and I, that deserve particular attention. NAEH and HUD have collated best practices for housing identification, including staffing, policies, and activities and case management (HUD, 2015; NAEH, 2016). NAEH suggests that programs should ensure that staff members are properly trained in housing identification services. Such training should ensure that staff progressively increase the supports provided in response to client needs and that staff set the subsidy level for rent at levels that enable clients to acquire a lease. It suggests that programs need to actively recruit and manage relationships with landlords. Strategies include signing master leases, guaranteeing short vacancy periods between tenants, and increasing the amount of security deposit provided. NAEH also recommends maintaining clearly defined relationships with employment and income programs to promote the capacity of clients to afford rent after program completion.

In a fully developed performance management system, managers would employ regular review meetings to focus on the poorly performing programs identified in this analysis. They could consult with program-level managers to compare their current practices to these best practices and develop appropriate strategies based on these comparisons. Once promising avenues are identified, system managers could work with program managers to implement these strategies and track their effectiveness through continued surveillance of the trends in performance metrics.

Prospects for Improvement

What is the potential magnitude for improved system-level performance if managers were to act on this analysis? To develop estimates, one needs to differentiate between two types of improvements: systemic improvements and error corrections. Systemic improvement moves the performance of an entire system to a higher level. Take, for example, a CoC with an average successful exit rate of 65 percent and in which no program in any year achieved higher than a 70 percent successful exit rate. For that CoC to raise its average rate to the NAEH benchmark of 80 percent would require systemic changes that increased the performance of providers beyond historical levels. Although this level of improvement is possible, it is challenging given that managers have no readily available models on which to build improvement strategies. Error corrections, in contrast, compare current performance to performance levels that have been achieved and seek to close the gap between current performance and past peak performance. The feasibility of these types of improvements is greater because the goals have been achieved previously in certain years and by certain programs, providing models to replicate.

Even with a more conservative focus on error correction improvements, the potential for improvements is significant. In this CoC, there have been programs that have met the 80-percent NAEH benchmark for successful exits. Thus, this goal is reasonable for the system as a whole. If programs were able to close one-half of the gap between their 2017 success rates and this benchmark, the number of clients stably housed would increase by 33 percent, from 747 to 995. Considering that HUD CoC grants have only increased at a 2.5-percent annual rate between 2010 and 2019, such performance improvements offer continuums a significantly greater avenue for increasing the program impacts compared to increasing budgets.

Discussion and Conclusions

The analysis presented here supports the contention that performance management can have significant positive effects on efforts to address homelessness in the United States. A guided search through performance metrics making comparisons over time and across subunits revealed weaknesses in program performance. Further process mapping then pinpointed the likely root cause of performance deficits as problems with identifying housing for program participants. Just partially closing the gap between low- and high-performing programs has the potential to improve overall program outcomes by between 30 and 40 percent.

The results also reinforce the findings of existing evaluation studies. As Rodriguez and Eidelman (2017) found that there is substantial variation in the performance of individual providers of RRH services, and the current analysis demonstrates how reducing the gaps between low and high performers can improve system-level outcomes. Also, the data presented here show that RRH can be an effective program. Certainly, in 2015, the year closest to the cohorts analyzed in the evaluation studies, the Sacramento program exceeded or came close to meeting the NAEH standards for housing placements and returns to homelessness. On the other hand, these data reveal a distinct decline in program performance from 2016 onward. These trends may be unique to Sacramento, given that its housing market has been impacted with particularly rapid increases in rents. Nevertheless, further study is warranted to see how pervasive these trends are especially given the strong evidence that homelessness is strongly impacted by tight housing markets (Glynn and Fox, 2019; Quigley and Raphael, 2001).

The adoption of robust performance management regimes does involve risks. First, the insights derived from these analytic tools can suffer from issues of internal validity. Managers may misattribute performance differences to program features that are in fact due to extraneous factors. The use of confidence intervals limits the dangers of misidentification of problems. Also, ongoing assessment of strategic initiatives can root out strategies based on faulty assessments of the underlying problems. Performance comparisons, however, do not fully control for alternative explanations for observed performance deficits such as differences in client characteristics and environmental factors. Future work could focus more on controlling for confounding factors through propensity score matching or other statistical controls. Nevertheless, the use of real-time programmatic data in performance management limits the use of random treatment assignment to control for differences in clients and environmental conditions. Consequently, performance management systems cannot replace rigorous program evaluations that take care to isolate program effects.

Second, as performance management systems strive to increase accountability and improve resource allocations, they create incentives to game the system either by cream-skimming, where programs boost outcomes metrics by enrolling easier to serve clients while turning away individuals who are less likely to succeed, or by outright distortion of reported data (Hood, 2006; Musso and Weare, 2020). Avoiding such perverse consequences requires deft management that emphasizes the degree to which performance management can lift the entire system to better achieve common goals over negative attention from rigid accountability. It is also important to maintain oversight over data quality to detect any issues in reporting.

These results from Sacramento are also not generalizable. The particular performance issues found in these data would not necessarily be found in other communities, and each community is likely to have its own set of idiosyncratic issues with program operations. In contrast, the methods pursued in this analysis, the process of broadly searching for performance outliers and then seeking to understand their root causes, can be replicated. The search for performance deficits will likely lead down different paths for other CoCs, and there may well be CoCs that meet or exceed NAEH benchmarks, leaving little room for improvement. Nevertheless, the magnitude of potential performance improvements, in this case, suggests that the opportunities for improvement in other CoCs are significant.

The main policy recommendation arising from this analysis is simply that more systems need to apply these analytic tools to the management of homelessness programs. HUD's development of Stella models is a major step forward in this process. Given that CoCs frequently lack expertise in data extraction and analysis, the Stella models provide decisionmakers powerful tools while avoiding imposing heavy data analytic costs on CoCs. On the other hand, there are limitations to the Stella model. It provides a specific set of analyses focused on subpopulations and pathways through the homelessness crisis system. The analysis presented here, in contrast, highlights the importance of analytic flexibility. Problems may pop up in multiple components of specific programs or a system as a whole. Thus, a broad approach that examines multiple key performance indicators is more likely to identify areas of concern. Then, a search for the root causes of performance deficits requires a combination of views into the data, including control charts, comparisons across time and programs, and process analysis. The relevant analyses are not evident until data anomalies are identified, making it difficult to define analytic packages ex-ante.

A second recommendation is the need to develop administrative controls of homelessness programs that are capable of effectively responding to data-analytic insights. Performance management is as much an exercise in leadership as in analytics (Behn, 2014). Major examples of successful performance management reforms involved skilled and committed leaders that operated in environments with centralized executive control. These examples include police departments with their military-like chain of command and parliamentary governments in other countries, such as New Zealand and Great Britain, where the ruling party has greater control to implement management changes (Moynihan, 2008). CoCs, in contrast, are loosely connected coalitions of providers and funders that lack a unitary executive function. Managing such governance networks with a focus on key performance metrics is a challenge, but one that must be confronted if communities are to realize the potential performance improvements illustrated by this analysis.

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