Evaluation of the Utah Department of Correction's (UDC) Implementation of the Statewide Adult Recidivism Reduction (SRR) Program

Phase Two Report
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Background

Program Introduction

The Bureau of Justice Assistance awards funding to federal and state correctional agencies for vital programs and systems reform aimed at improving the reentry process through the Second Chance Act (SCA). The SCA legislation was signed into law on April 9, 2008 and designed to help states take a systematic, sustainable approach to establish policies and practices that will improve recidivism outcomes for individuals returning from federal and state prisons, local jails, and juvenile facilities. In order to receive funding, correctional agencies must invest in implementing evidence-based programs and practices that have been shown to reduce recidivism. The initiatives selected by correctional agencies must address three primary areas: 1) use of risk/needs assessments to inform resource-allocation decisions and individual case plans, 2) evaluate recidivism-reduction programs, practices, and trainings and ensure that they are implemented with fidelity, and 3) implement community supervision policies and practices that promote successful reentry.

The Utah Department of Corrections (UDC) was awarded funding through the SCA to implement an initiative to improve the reentry process for individuals returning to the community from prison. It was through this funding that UDC designed and implemented the Statewide Adult Recidivism Reduction (SRR) initiative. The main goal of SRR is to reduce the criminogenic risks of justice-involved individuals reentering the community. In order to achieve this, UDC is implementing more frequent/timely LS/RNR assessments as well as developing individualized case action plans for parolees based on current risk/needs assessment results. The case action plans consist of evidence-based programming, career building opportunities, and strong support systems that begin upon intake into prison, evolve throughout their time in custody, and continue upon release into the community.

As of 2014, approximately 62% of UDC inmates released from prison return within 3 years of release. SRR was designed to have the greatest impact on high or intensive risk individuals given that they are responsible for the majority of returns to prison in Utah. High to intensive risk individuals accounted for 84% of returns to prison in 2014. UDC has set a goal to reduce statewide recidivism by 10% within the first two years of implementing SRR initiatives and 25% within a 5-year period.

Evaluation Plan and Objectives

The Utah Criminal Justice Center (UCJC) contracted with the Utah Department of Corrections (UDC) to evaluate several aspects of the Statewide Adult Recidivism Reduction (SRR) Programs' initiatives and their hypothesized effects. This report is divided into sections that address each of the following objectives related to SRR:

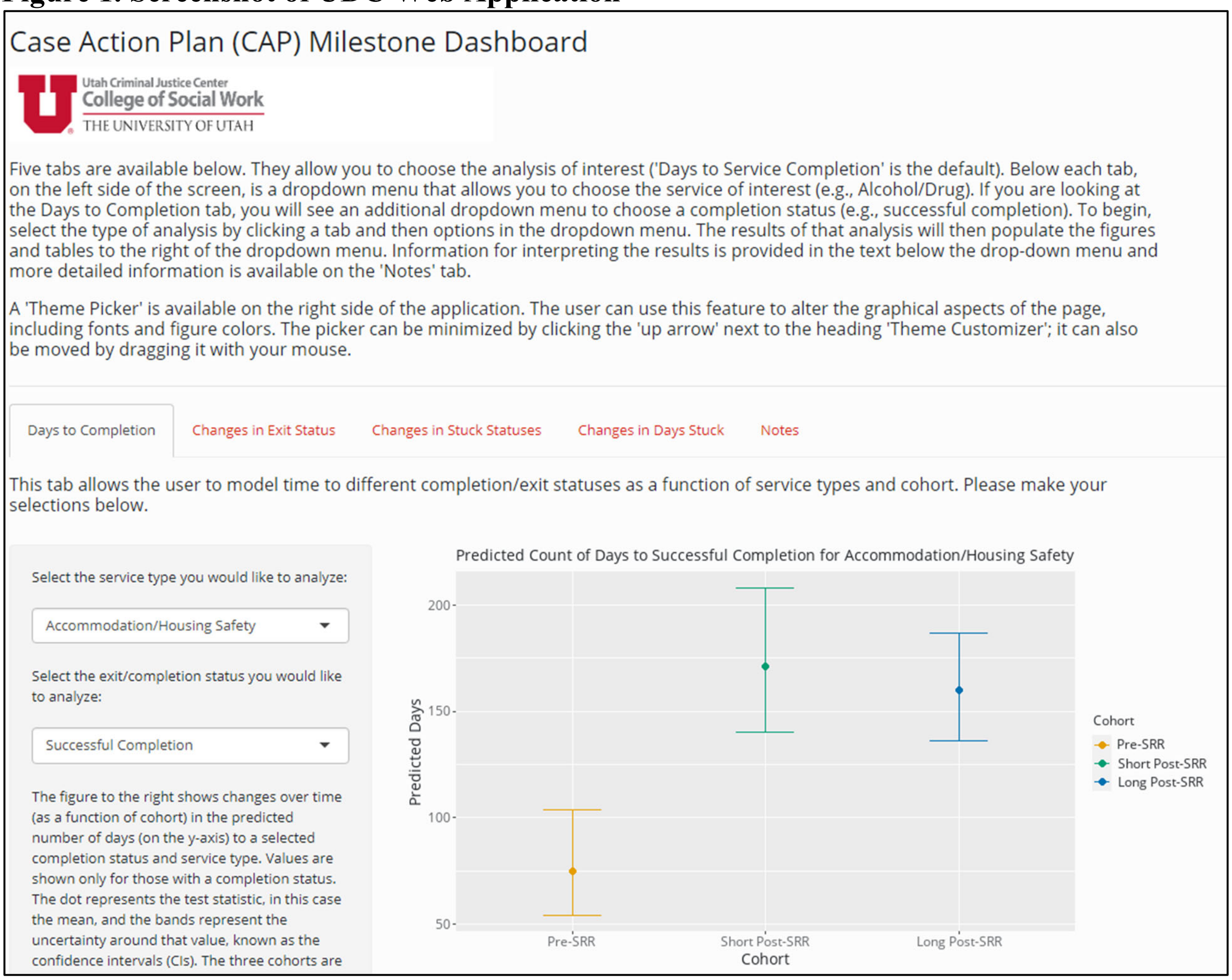
1. An evaluation of how well case action plans (CAPs) align with risk assessments along with documentation of improvements in alignment over time (by month).

2. A cohort analysis to examine whether there has been a statistically significant reduction in the rate of recidivism across the cohorts (i.e., pre-SRR; short-term post-SRR; long-term post-SRR).

As noted in more detail in the relevant section below, the second objective could not be addressed as proposed in the scope of work due to potential confounders between the cohorts (e.g., historical events) as well as limitations related to using propensity score matching (e.g., it often drops too many unmatched cases across groups). In order to address these issues, covariates were included in the modeling process to examine recidivism; modifications are discussed in more detail below.

In addition to this final report, UCJC developed a separate web application for UDC to utilize in planning and evaluation of the SRR initiative (see Figure 1 for a screenshot of the application). The web application is described here for expositional purposes but is only available on a secure platform hosted by shinyapps.io[1].

Figure 1. Screenshot of UDC Web Application



[1] Permission to view and utilize the application is required from UDC and UCJC. Please contact Dennis Franklin at UDC (dfranklin@utah.gov) to request permission.

Some of the questions UDC was interested in addressing regarding the effects of SRR were exploratory in nature and involved a large number of statistical models that made a web application more feasible given its flexibility over a static document. The web application addresses the following issues: days to service completion as a function of service type (e.g., antisocial patterns, cognitive/life skills, education, etc.) and exit status (i.e., successful, unsuccessful, incomplete – no fault of offender), changes in exit status frequency as a function of service type, changes in service types becoming stuck, and changes in the number of days for which service types were stuck.

Each tab in the application provides the ability to produce a large number of statistical models. For example, the "Days to Completion" tab allows the user to select 16 service types and three exit statuses for a total of 48 statistical models. For each model, the user can download the figure produced by the code, the model-based predictions, and the statistical significance tests. Notes are available as a separate tab to aid interpretation. The application will be available for three years from the date of this report or until UDC requests its removal.

Needs-to-Case Action Plan (CAP) Alignment

Purpose

One of the aims of the SRR initiative is to enhance how well CAPs align with risk/need assessment results. It is hypothesized that service-to-needs alignment will improve over time as probation agents become accustomed to the changes in the CAP process. Because the system to track alignment is relatively new, the analysis will track alignment dating back to July 2020, the time at which the new system was well-established. Additionally, the analysis examined whether there were improvements in alignment by month since July 1, 2020.

Analytic Approach

UDC staff provided UCJC with data containing the following information: parolee information; LS/RNR assessment results; CAP action steps; CAP goals; CAP classes; and CAP classes and programs. The file containing parolee information contained 8,781 unique cases across 6,536 individuals. For the purposes of the analyses that follow, anyone who was on parole after July 1, 2020 (i.e., the date chosen by UDC to represent full implementation of the system to track alignment) was included in the final sample.

UCJC also received LS/RNR assessment data for parolees. These data were merged with parolee information for cases with an active parole term after July 1, 2020. Given that parolees may have multiple LS/RNR assessments, the assessment closest to the parole start date was selected for analysis. The next step involved joining the CAP-related events with the parolee and LS/RNR data. CAP events that occurred before July 1, 2020 and CAP events that occurred outside of the parole term for each case were removed from the data. These data were merged with the parolee and LS/RNR data. The final analytic sample contained 11,377 CAP events among 2,092 cases or 1,999 parolees. Because people could be released from prison to parole more than once, there was some duplication across people.

For these analyses, data were analyzed in two ways. First, data were analyzed at the case level (n=2,092). Several different outcomes related to service-needs alignment were examined in this report. Drawing from recent studies conducted by Drawbridge et al. (2020) and Nelson and Vincent (2018), a variable to capture three outcomes related to service-need alignment (i.e., good service match, overprescription, and underprescription) was created. In order to code a variable as a good service match, it was necessary to capture whether a need area was present. A need area was coded as being present if it was scored between moderate and intensive risk. Need areas scored as low risk were coded as being not present. A service-to-need match was coded as being a good match if the need area was identified as being present and at least one service referral was assigned to address that specific need, or if there was the absence of a need area and no service referrals were made for that need. The two remaining outcomes are considered to be a "bad match". Overprescription is defined as the assignment of at least one service to a parolee that targets a need area that was identified as being absent. Conversely, underprescription occurs when a parolee did not receive a service that aligned with a need area that was scored as present. Each of these outcomes is examined for each LS/RNR criminogenic need domain.

The case-level analysis also considers whether parolees had at least one of their top three criminogenic need areas met. UDC developed a priority rating for criminogenic needs areas based on the individual's assessment results (i.e., low thru intensive) and whether the domain falls within the big four of the central eight criminogenic need areas (see, Bonta & Andrews, 2017). The criminogenic needs areas categorized as the big four include: criminal history, antisocial pattern, procriminal orientation/attitude, and antisocial companions. A set of variables was created to capture the top three domains for each case as well as a variable that identifies how many of the top three domains were met. The analysis examines whether there were differences in the prevalence of having top priorities met by demographic characteristics and LS/RNR overall risk level. Additionally, the analysis assesses for significant differences in the number of criminogenic needs present, number of criminogenic needs met, and total number of services received by LS/RNR overall risk level.

Second, the data were analyzed at the CAP-event level to examine how well CAPs align with LS/RNR assessments over time. This analysis required UCJC to capture whether each CAP event addressed a criminogenic need area for that individual. A variable was created to capture the proportion of services that matched needs to the total number of services received by month (i.e., July 2020 thru August 2021). Between July 2020 and August 2021 there were 11,349 CAP events. These findings are presented in Figure 2 (described more below), which also includes a regression line to represent the overall trajectory. A line graph is utilized to display the changes in the percentage of CAP events that addressed present criminogenic needs (i.e., dependent variable) by time in months (i.e., independent variable). The regression line expresses the relationship between these two variables and plots the predicted values of the dependent variable based on knowledge of the y-intercept and regression coefficient. The regression coefficient is interpreted as the estimated change in the dependent variable that is associated with a one-unit change in the independent variable. Additionally, a binary logistic regression model was estimated to examine whether there was a change in the odds of service-to-need matching over time.

Analytic Results

Case Level Service-to-Need Matching

Service-to-need matching has increasingly received attention from criminal justice stakeholders and researchers. In this section the analysis examined whether cases had a criminogenic need present (i.e., moderate to intensive) across each of the LS/RNR domains and whether this aligns with the services that were received during parole. Table 1 below provides an overview of the cases with moderate to intensive need by LS/RNR domains. The criminal history domain was by far the most common need area among the sample (96.1%). There were several other domains that were particularly common need areas in the sample: companions, leisure/recreation, and antisocial patterns (88.1%, 87.1%, and 75.8%, respectively). The majority of cases in the sample also had a need area present in the education/employment and family/marital domains (69.3% and 68.9%, respectively). The alcohol/drug problems domain and the procriminal attitude/orientation domain were the least common of the central eight need areas in the sample (51.8% and 45.7%, respectively).

Table 1: Cases with Moderate to Intensive Need by LS/RNR Domain (n=2,092)

Need area	n (%)
Criminal History	2,011 (96.1)
Education/Employment	1,449 (69.3)
Family/Marital	1,441 (68.9)
Leisure/Recreation	1,823 (87.1)
Companions	1,843 (88.1)
Alcohol/Drug Problems	1,084 (51.8)
Procriminal Attitude/Orientation	957 (45.7)
Antisocial Pattern	1,586 (75.8)

To examine service-to-need alignment, the analysis compares whether the aforementioned need areas are matched with appropriate services. Table 2 below illustrates the percentages of good matches, and bad matches including underprescriptions for persons with a moderate to intensive need by need area and overprescriptions for persons with no need by need area. Good matches ranged from 7.5% in criminal history to 58.1% in alcohol/drug problems. At the lowest end, 7.5% of cases who had a need in the criminal history domain received at least one service referral to address this need or did not have a need and did not receive a service referral for it. On the highest end, 58.1% of cases with a need in the area of alcohol/drug problems received a service referral to address it or did not have a need in this area and did not receive a service referral for it. Following good matches for alcohol/drug problems, good matches for the remaining domains were as follows: 55.9% for procriminal attitude/orientation, 33.7% for family/marital, 30.7% for education/employment, 27.9% for antisocial pattern, 21.2% for companions, and 18.2% for leisure/recreation.

Overprescription of services for cases that did not have a need in an area varied quite drastically by domain. Overprescription was most common among service referrals for an alcohol/drug problem. Of the 1,008 cases that did not have an alcohol/drug problem need present, 743 received a service referral for alcohol/drug problems (73.7%). Overprescription was also more prevalent with respect to the procriminal attitude/orientation domain. Specifically, 51.6% of cases that did not have a procriminal attitude/orientation need received a service referral in this area. Overprescription was drastically less common among the remaining LS/RNR domains. Less than 10% of cases that did not have a need in either the criminal history, education/employment, family/marital, leisure/recreation, companions, or antisocial pattern domain received a service to address one of these need areas.

Underprescription was far more common than overprescription and occurred across a greater number of domains. Underprescription occurs when an individual has a need in a criminogenic need area and does not receive a service referral to address it. Of the 1,449 cases that had a need present in the area of education/employment, 100% of them did not receive a service to address this area. Underprescription was also an issue with respect to criminal history, family/marital, antisocial pattern, leisure/recreation, and companions domains. Underprescription occurred in at least 88 percent of cases in each of these domains. Underprescription was least common in the procriminal attitude/orientation and alcohol/drug problems domains (35.1%, and 12.3%, respectively).[2]

Table 2: Service Matching to LS/RNR Identified Need Area (N=2,092)

Need area	No need, n (%)	Need present, n (%)	Good service match, n (%)	Over prescription, n (%)	Under prescription, n (%)
Criminal History	81 (3.9)	2,011 (96.1)	157 (7.5)	2 (2.5)	1,933 (96.1)
Education/Employment	643 (30.7)	1,449 (69.3)	643 (30.7)	0 (0)	1,449 (100)
Family/Marital	651 (31.1)	1,441 (68.9)	706 (33.7)	27 (4.1)	1,359 (94.3)
Leisure/Recreation	269 (12.9)	1,823 (87.1)	381 (18.2)	22 (8.2)	1,689 (92.6)
Companions	249 (11.9)	1,843 (88.1)	443 (21.2)	13 (5.2)	1,636 (88.8)
Alcohol/Drug Problems	1,008 (48.2)	1,084 (51.8)	1,216 (58.1)	743 (73.7)	133 (12.3)
Procriminal Attitude/Orientation	1,135 (54.3)	957 (45.7)	1,170 (55.9)	586 (51.6)	336 (35.1)
Antisocial Pattern	506 (24.2)	1,586 (75.8)	584 (27.9)	21 (4.2)	1,487 (93.8)

Note. Percentages for columns were calculated using different denominators. A criminogenic need domain being absent or present, and the rates of good service matching are reflected in the percentage of cases out of the entire sample (n=2,092). The percentage of cases that resulted in overprescription includes only cases with the need area absent (i.e., No need); whereas, underprescription is out of the percent of cases with the need area present (i.e., Need present). LS/RNR is the Level of Service/Risk, Need, Responsivity assessment instrument.

Priority Criminogenic Need Areas

When considering whether the parolees had any of their criminogenic needs met, 74.4% of the 2,092 cases had at least one of their criminogenic needs addressed. That is not to say that the 26.6% of cases did not receive any services to address criminogenic needs; however, this indicates that the services received did not address the present needs of the parolees (i.e., need areas rated moderate to intensive risk).[3] The prevalence of cases having at least one of the top three criminogenic-need priorities met was also examined. Of the 2,092 cases, 1,030 cases did not have one of the top three needs addressed (49.2%). The remaining 1,062 cases had at least one of the top three needs met. Approximately 43% of cases had one of the top three priority needs met. 7.2% of cases had two of the top three needs addressed and 0.4% had all three of the top needs met.

The analysis also explored whether there were differences in the prevalence of a case having a top three need area addressed by demographic characteristics and risk-level (see Table 3 below). Cases involving males were slightly less likely to have at least one of the top three needs areas met when compared to females (49.8% and 55.3%, respectively); although this difference was not significant at p-value ≤ 0.05 ($p=0.052$). Cases involving White parolees were slightly more likely to have at

[2] *Note*. It is possible that parolees may have been enrolled in services that addressed their present criminogenic needs prior to July 1, 2020. Given that the system to track alignment was not fully implemented until July 1, 2020, CAP events were only analyzed if they occurred on or after this date. CAP events also had to occur during the parole term for each case. This could artificially increase the percentage of cases that did not receive services to address any of their criminogenic needs. For example, 3.85% of all CAP events that UDC sent targeted education/employment. For CAP events that occurred on or after July 1, 2020, 1.31% targeted education/employment. After removing CAP events that occur outside of the parole term for each case, the number of CAP events that addressed education/employment was reduced to 0.

[3] *Note*. All 2,092 cases had at least one CAP event that addressed a LS/RNR domain, of which 26.6% were not good matches based on the LS/RNR assessment results.

least one of the top three needs addressed compared to cases involving Non-White parolees (52.3% and 49.8%, respectively). This difference was also not statistically significant at p-value ≤ 0.05 (p=0.064).

Several interesting findings emerged when examining priorities met by risk level. As would be expected, a greater percentage of cases involving parolees who scored intensive on the LS/RNR had at least one of the top three priority need areas addressed compared to lower risk levels (62.2% of intensive risk parolees). Although there were only 30 cases scored as low risk on the LS/RNR, 53.3% had at least one of the top three priority need areas addressed compared to 46.7% of cases who scored moderate risk and 46.1% who scored high risk. These differences are statistically significant and the measure of association indicates a small effect. According to a standard measure of effect size suggested by Cohen (1988), a phi or Cramer's V value of 0.10 is considered a small effect, 0.30 a medium effect, and 0.50 a large effect. Based on the risk-need-responsivity model, one could expect that a greater percentage of moderate- and high-risk cases would have one of their top three priority need areas addressed.

Table 3: Criminogenic Need Priorities Met by Case Characteristics (n=2,092)

	No Top Priorities Met n (row %)	At Least One Top Priority Met n (row %)	χ^2 (p-value)	Phi/Cramer's V
Gender			3.8 (0.05)	0.04
Female	169 (44.7)	209 (55.3)		
Male	861 (50.2)	853 (49.8)		
Race			3.4 (0.06)	0.04
White	622 (47.7)	683 (52.3)		
Non-White	408 (51.8)	379 (48.2)		
Overall Risk Level			42.0* (<0.001)	0.14
Low	14 (46.7)	16 (53.3)		
Moderate	226 (53.3)	198 (46.7)		
High	573 (53.9)	491 (46.1)		
Intensive	217 (37.8)	357 (62.2)		

* p-value < 0.001

Note. Criminogenic need priority areas were determined by Utah Department of Corrections and consider the domain risk score/level as well as whether the domain falls within the "Big Four" (see Bonta & Andrews, 2017). Top priority met is defined as having met at least one of the top 3 priority criminogenic areas.

Services Received and Criminogenic Needs by Risk Level

In accordance with the risk-need-responsivity model, criminogenic needs and services should vary by an individual's risk level. A series of ANOVA (analysis of variance) were estimated in order to examine whether there were significant differences in the number of needs and services received by risk level. The first analysis examines whether there are differences in the number of present needs by risk level. The findings from the ANOVA indicate that there is a statistically significant difference in the mean number of present needs between the different risk levels (F=1813.14; p-value < 0.001). While ANOVA results reveal that there is a significant relationship between these two variables, it does not tell us where these differences exist. If the F-test is significant a post-hoc analysis can be used to determine where significant mean differences exist across the categories/levels of the independent variable. One commonly used post-hoc analysis is the honestly significant difference (HSD) test developed by John Tukey. This test defines the value of the difference between all pairwise comparisons that is required to reject the null hypothesis at a given p-value. Table 4 below displays the results from pairwise comparisons between mean number of present needs and risk level.

The findings from the Tukey HSD post-hoc analysis reveal differences that align with what would be expected based on the risk-need-responsivity model. Specifically, the mean number of present needs was higher as the risk-level increased. The mean number of present needs for parolees who were scored as low risk was 1.67. For moderate risk parolees, the mean number of present needs was 3.56. On average, high-risk parolees had 5.92 present needs. Intensive-risk parolees had an average of 7.55 present needs. In the "Comparison" column, the first risk level category listed is the reference category, meaning mean differences are interpreted relative to that category. The last column contains the p-value, which represents whether the mean difference was statistically significant. The mean difference between all comparisons of present needs by risk level was statistically significant (p-value ≤ 0.05).

Table 4: Tukey HSD Pairwise Comparisons for Present Needs by Risk Level

Outcome	Comparison	Mean Difference (95% CI)	S.E.	p-value
Sum Present Needs	Intensive - High	1.62 (1.50 – 1.74)	0.05	0.000
	Intensive- Moderate	3.99 (3.84 – 4.14)	0.06	0.000
	Intensive - Low	5.88 (5.45 – 6.31)	0.17	0.000
	High - Moderate	2.36 (2.23 – 2.50)	0.05	0.000
	High - Low	4.26 (3.83 – 4.69)	0.17	0.000
	Moderate - Low	1.89 (1.46 – 2.33)	0.17	0.000

Note. Sum of present needs includes only need areas that were scored moderate to intensive.

Given the previous findings, one would expect the number of services received to vary similarly by risk level. The findings from the ANOVA reveal that there was a statistically significant difference in the average number of services received by risk level ($F=12.71$; p-value < 0.001). The mean number of services received by low-risk parolees was 3.13, 4.36 for moderate-risk parolees, 5.50 for high-risk parolees, and 6.25 for intensive-risk parolees. In order to examine which of these groups differed in the number of services received, a Tukey HSD post-hoc test was conducted (Table 5 below). The findings reveal that there was a significant difference in the mean number of services received between the following groups: intensive and high; intensive and moderate; intensive and low; and high and moderate (p-value ≤ 0.05).

Table 5: Tukey HSD Pairwise Comparisons for Services Received by Risk Level

Outcome	Comparison	Mean Difference (95% CI)	S.E.	p-value
Number Services Received	Intensive - High	0.75 (0.06 – 1.44)	0.27	0.028
	Intensive- Moderate	1.89 (1.03 – 2.75)	0.33	0.001
	Intensive - Low	3.11 (0.61 – 5.62)	0.98	0.008
	High - Moderate	1.14 (0.37 – 1.91)	0.30	0.001
	High - Low	2.35 (-0.11– 4.84)	0.96	0.068
	Moderate - Low	1.23 (-1.30– 3.75)	0.98	0.598

Lastly, the analysis examined whether there were differences in the number of present needs addressed by risk level. Based on the risk-need-responsivity model, the expectation would be that these would mirror a pattern similar to the analysis examining number of present needs by risk level. Also, the number of present needs met for parolees assessed as moderate through intensive risk would likely be greater than or equal to a value of one. The findings from the ANOVA revealed a significant difference in the number of present needs that were addressed by risk level ($F=163.14$; p-value < 0.001). On average, low-risk parolees had 0.33 of their needs met, 0.59 for moderate risk, 0.96 for high risk, and 1.55 for intensive risk. The Tukey HSD post-hoc test was conducted to examine the differences between the groups (Table 6 below). Of the six possible comparisons five were significant at p-value ≤ 0.05, with the only exception being moderate and low. These findings do reveal a similar pattern as the analysis of the number of needs by risk level suggesting that as risk level increases so to do the number of present needs as well as the number of needs that are addressed by services.

Table 6: Tukey HSD Pairwise Comparisons for Number of Present Needs Met by Risk Level

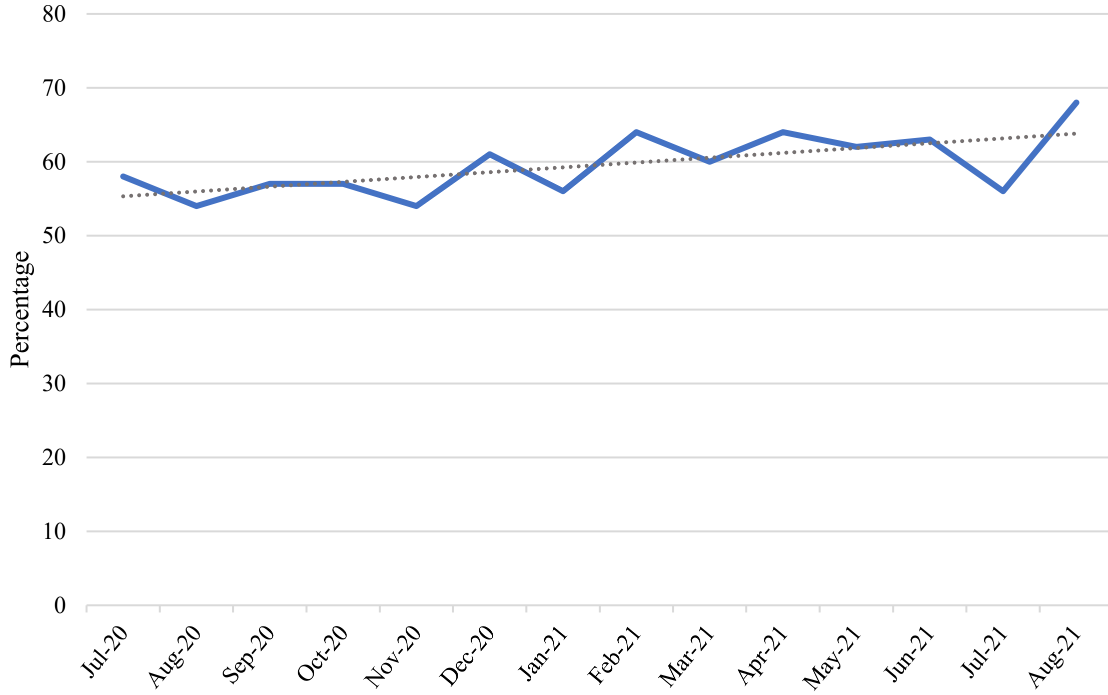
Outcome	Comparison	Mean Difference (95% CI)	S.E.	p-value
Sum Present Needs Met	Intensive - High	0.60 (0.49 – 0.69)	0.04	0.000
	Intensive- Moderate	0.96 (0.84 – 1.08)	0.05	0.000
	Intensive - Low	1.22 (0.87 – 1.57)	0.14	0.000
	High - Moderate	0.37 (0.27 – 0.48)	0.04	0.000
	High - Low	0.63 (0.28 – 0.97)	0.13	0.001
	Moderate - Low	0.25 (-0.10– 0.61)	0.14	0.250

Note. Sum of present needs met includes only need areas that were scored moderate to intensive.

Service-to-Needs Matching over Time

The final set of analyses in this section considered whether service-to-needs alignment improved over time. For these, all CAP events recorded between July 2020 and August 2021 (n=11,349) were included in the analysis. Figure 2 illustrates the percent of service-to-needs matching by month. The solid blue line represents the month to month change in the percent of service-to-needs matches. The dotted line has been fitted to these data and illustrates the overall trend. Although there appears to be quite a bit of variation in percent of service-to-needs matches from month to month, the trend line indicates that there has been a slight but steady increase in matches from July 2020 to August 2021. The percent of matches ranges from 54% in August and November 2020 to 68% in August 2021, which represents a 25.93% increase. Based on the trend line, the percent of matches increases by approximately 15% from July 2020 to August 2021.

Figure 2: Percent Service-to-Needs Matches by Month



Lastly, a binary logistic regression model was estimated to examine the relationship between whether criminogenic areas were met and time (months). The findings indicate that the probability of criminogenic need areas being met increases by 1.026 times for every one unit increase in months ([exp]B=1.026; S.E.=0.005; p-value < 0.001). The exp(B) value is also known as the odds ratio, and a value of 1.026 indicates that the odds of criminogenic needs areas being met increases by 2.6% for every one-unit increase in months over the study timeframe.

Recidivism

The next set of analyses describe recidivism outcomes for the SRR project. Recidivism, for purposes of the analysis, was defined as a return to prison for either a parole violation or committing a new offense. Data for this section were combined from two sources. UDC provided data on both parole violations and new offenses. Data on new offenses was provided when the new offenses occurred during supervision and UDC was, therefore, aware of them. The Bureau of Criminal Identification (BCI) provided more complete records related to new offenses, as BCI records extend to all offenses in the state and beyond supervision.

In some instances, the two systems (BCI and UDC) did not agree on whether or when a new offense occurred. If a new offense was found in one system, but not the other, the new offense was retained for analytic purposes. Similarly, if one system had a different date for a new offense relative to the other, the earlier date was adopted.

Data were analyzed using three cohorts of equal length[4]. The first cohort was labeled "pre-SRR" (n = 2,084) and included all parolees released from prison in the date range of 11/01/2018 – 6/30/2019. This cohort received no services related to SRR. The "short-term SRR" cohort (n = 2,339) included paroles released in the date range from 7/01/2019 – 2/28/2020. This cohort received some of the SRR services, as the SRR program, and its components, were rolled out gradually. The "long-term SRR" cohort (n = 2,352) included parolees released during the date range from 3/01/2020 – 10/31/2020; this cohort was marked by completion of the rollout of SRR-related services. The total sample size, across all cohorts, was 6,775.

As seen above, the cohorts had varying periods of exposure. Data related to recidivism were available through 8/24/2021; accordingly, the earliest release in the pre-SRR cohort could have been followed for 1,027 days (the difference between 8/24/2021 and 11/01/2018). By comparison, the last release in the long-term SRR cohort could have been followed for only 297 days.

Models that follow utilized survival analysis, which is one statistical method that can accommodate varying exposures. Models were truncated to 541 days, which corresponds to the longest possible exposure period within the long-term SRR cohort (the difference between 8/24/2021 and 3/31/2020). Accordingly, all individuals were followed for recidivism outcomes (parole violations or new offenses) for a period of up to 541 days, though some long-term cohort members were censored before 541 days; that is, they did not all have 541 days of post-release observation time. Censoring of cases is not, however, a problem for survival analysis models.

Analytic Caveats

Because this evaluation utilized a cohort-based analysis, the most important caveat to consider when evaluating the outcomes presented below is that any cohort-based analysis (or any

[4] Some individuals were released more than once. All cases were retained rather than taking the first release because taking the first release among cases that were known to have been released again (those who clearly recidivated) would have made earlier cohorts look artificially more at risk.

longitudinal analysis) can suffer from history effects, which are a threat to the internal validity[5]. Although this research attempts to account for some differences across the cohorts in terms of covariates that are related to recidivism (more detail provided below), it is impossible to account for all differences and it is likely that historical differences (e.g., policies in criminal justice or within UDC regarding supervision, for example) exist that also might have impacted the rates of recidivism. Unfortunately, this possibility cannot be entirely ruled out in a longitudinal study involving cohort-based analyses.

A second consideration, which is also a historical effect, is the impact of the Covid-19 pandemic. It is difficult to quantify the impact the pandemic had on recidivism within UDC, but it should be noted that the long-term cohort coincided nearly entirely with the worst of the pandemic to date and that cohort's observation period overlapped the pandemic to a greater extent than any other cohort. UDC has indicated that, for a period of time during 2020, face-to-face visits and fugitive roundups were reduced or halted altogether; this fact could impact returns to prison due to parole violations. UDC began to gradually resume in-person reporting, center operations, treatment, and apprehensions in the Spring of 2021. This report discusses the potential impact of these modifications to typical operations in the summary of this recidivism section (below).

Modeling Options

Depending on the field or area of study, there is oftentimes benefit to knowing if, in addition to whether a treatment might have prevented an event, the treatment also delayed an event. This is obvious in the case of medical treatments for (as an example) cancer, where delaying reoccurrence or death may be more practical than preventing it indefinitely. Although perhaps less obvious, delaying reoccurrence also has benefit in terms of recidivism by, for example, reducing the overall extent of a criminal record and concomitant disruptions to life (e.g., family and employment) as well as reducing the number of victims of crime. To address whether SRR implementation was related to both preventing the occurrence of return to prison and also delaying the occurrence, survival analysis (described below) was used to examine time-to-event(s).

Because individuals can recidivate for multiple reasons (parole violations and new offenses), the models needed to consider the impact of these competing risks. Within survival models, there are several ways one can analyze data to address the multiple ways one can recidivate. These modeling options are briefly reviewed below.

The simplest method of dealing with competing risks is to treat any failure event (parole violations and new offenses combined) as the outcome of interest. *Event Free Survival (EFS)* takes this approach by combining returns due to parole violations or new offenses into a failure. EFS ignores whether predictors, in this case cohorts, impact the outcomes differently.

In contrast to the EFS approach, a *Cause Specific Hazard* (CSH) model describes the probability of one event (e.g., return to prison for a parole violation) in the complete absence of the other event (e.g., committing a new offense). This type of model should be used and interpreted with caution. It represents the occurrence of a focal event in a hypothetical context in which the other event does

[5] Internal validity refers to the ability to conclude that an independent variable, such as cohort, is responsible for the observed effect on the dependent variable, or recidivism.

not occur. Because of this, the event rate for the focal event is overestimated compared to the reality in which multiple failure possibilities exist. This type of model is common in cancer research where causes of death due to other events (e.g., heart disease) are not of direct interest to a cancer treatment.

Finally, in a *Cumulative Incidence Function (CIF)* approach, the occurrence of the competing risk is accounted for when estimating the occurrence of the other event of interest. In the context of recidivism, it provides the actual probability of failure to a particular cause rather than the hypothetical probabilities of failure to one event in the absence of the other causes' existence.

The decision of which model to use is both practical and statistical in nature. If an EFS approach is adopted, the analyst is essentially saying a failure due to any cause is of interest and there is no additional benefit to knowing whether a program, in this case SRR, impacted the rate of return differently by risk type (parole violation or new offense). Though not always the case, in recidivism, sometimes a treatment program does impact the two event types differently. For example, increased supervision can reduce new offenses, but the increased level of scrutiny can increase the likelihood of parole violations.

If a CSH approach is adopted, the analyst is implicitly stating that one event is of greater interest than another. In this case, the two events are modeled separately, as if they do not occur in a related manner. While this works well in some contexts, it is not a particularly good fit for recidivism because both types of returns to prison are of direct interest. Because both events are of direct interest, the modeling approach for this report adopted the CIF approach. The purpose of this analytic choice is that the competing reasons a person returns to prison are important in terms of evaluating SRR.

Model Interpretation

The models that follow compare cohorts using CIF time-to-event survival analyses. Survival models provide a coefficient known as a Hazard Ratio (HR), which is a ratio of the rate of event occurrence in one group compared to another. One nice feature of the HR is that it is also an effect size. While p-values are dependent on sample size, effect sizes are mostly independent of sample size. In a sufficiently large sample, even a trivial effect can be significant. For that reason, effect sizes are often more useful in determining the true effect of an intervention. Hazard ratios are interpreted according to the following effect size standards: small = 1.22, medium = 1.86, and large = 3.00 (Olivier, May, & Bell, 2017). In the social sciences, effect sizes are most often between small and medium.

Modeling

Originally, the modeling process intended to use Propensity Score Matching (PSM) to match similar cases across the three cohorts. However, PSM is not always a feasible analytic option once the actual data are received and considered, and it was not feasible in this case for at least two reasons. First, the use of cohorts meant that individuals experienced different historic events (e.g., policies) in the period surrounding their release. Policy-related data were not available for matching; however, even if they were, it is difficult to quantify the effect of policy changes at the person-level. Second, PSM drops cases that cannot be matched across groups. In this case, the number of cases that would have been lost was too large to make PSM viable.

Because of these issues, the modeling process did not use PSM, but did utilize covariates in the modeling process. The covariates were adopted based on their statistical importance related to both recidivism and differences across cohorts. The variables utilized as covariates included: the number of arrests in the two-year period occurring before the incarceration that qualified a person for a cohort, the severity of the most severe offense committed before incarceration, age at incarceration, and the number of disciplinary infractions occurring while incarcerated[6]. Models below are interpreted conditional on these covariates. The covariates were scaled and centered, and, accordingly, one can interpret the effect of SRR as occurring at the average value of each of the four covariates. For example, when age at incarceration is centered, the effect of each cohort on recidivism is interpreted as the effect at the average value of age[7].

Table 7 below provides a summary of the CIF approach modeling time-to-event occurrence. The table utilizes pairwise comparisons. That is, each cohort is compared to every other cohort. In the "Comparison" column, the first cohort is the reference cohort, meaning coefficients are interpreted relative to that cohort (explained further below).

Although the CIF approach models the events cumulatively, the models provide a coefficient for each outcome (though each coefficient is derived considering each event in the presence of the other). The column labeled "Coefficient" is in a transformed metric and is generally not intuitive to interpret and so it is ignored here, but is provided for a technical audience. The column labeled "S.E." provides the standard error around the point-estimate in the coefficient column, which can be thought of as a measure of uncertainty in that estimate. The exponentiated coefficient is the Hazard Ratio (denoted "HR" in the table). This coefficient is generally easier to interpret, and a detailed explanation of its meaning is provided below when interpreting the model. In parentheses following the HR, the 95% confidence interval of the HR (effect size) is provided. This can be thought of as a measure of uncertainty in the effect size and it is considered not significant (by traditional standards) if the value crosses 1.0. The "p-value" indicates the significance of the comparison, and values less than .05 are typically considered significant.

Parole Violations

Beginning with parole violations, and using the criteria outlined above, a non-significant effect was found for the short-term SRR cohort compared to the pre-SRR cohort and, and a significant effect, though below small (using the aforementioned HR criteria above), was found for the long-term SRR cohort compared to the pre-SRR cohort. In the case of the short-term SRR cohort compared to the pre-SRR cohort, the HR value of 0.922 indicates that, accounting for returns due

[6] Disciplinary infractions are recorded in UDC's system as types A, B, C, or D. Types A and B are the most severe, while types C and D can be quite minor. For the models, only types A and B were considered, and the number of infractions was the sum of these two types. The sum was not adjusted for duration of incarceration because higher sums were also a proxy for longer periods of incarceration.
[7] Models were run with and without covariates in a sensitivity analysis. Model coefficients changed little with the covariates removed, but the models with them included were adopted because of the need to partially account for differences across the cohorts.

to new offenses as well as the covariates, the short-term SRR cases returned to prison on parole violations at a rate 7.8% (or 1 – 0.922) slower than the pre-SRR group. One can invert the HR below 1.0 to arrive at an effect size: 1/.922 = 1.09, which is below small. For the long-term SRR cohort compared to the pre-SRR cohort, the long-term SRR cohort members returned to prison on parole violations at a rate 13.0% (or 1 – 0.870) slower than the pre-SRR cohort. This effect is statistically significant at p = 0.016. One can again invert the HR below 1.0 to arrive at an effect size: 1/.870 = 1.15, which is near, but still below small. There was not a statistically significant difference between the long- and short-term cohorts (p = 0.310). Although the short-term cohort returned to prison on parole violation at a rate of 1.06 times (or 6%) faster than the long-term cohort, the correct interpretation is to assume no difference in the actual rate of return. The effect size is again below small.

New offenses

For new offenses, none of the results were significant, so although the short- and long-term cohorts committed new offenses at rates slightly greater than the pre-SRR cohort (1.02 and 1.04 times faster, respectively), because the results are not significant, the correct interpretation is that there is no difference between the cohorts in the rate of committing new offenses. Both effects were also well below small. The short-term cohort committed new offenses at a rate 1.6% slower (1 - .984) than the long-term cohort; however, the result is not significant and so, again, the correct interpretation is that there is no difference between the cohorts in the rate of committing new offenses. One can again invert the HR below 1.0 to arrive at an effect size: 1/.984 = 1.02, which demonstrates no effect.

Table 7: Summary of CIF and EFS Survival Models Through Maximum Observed Time

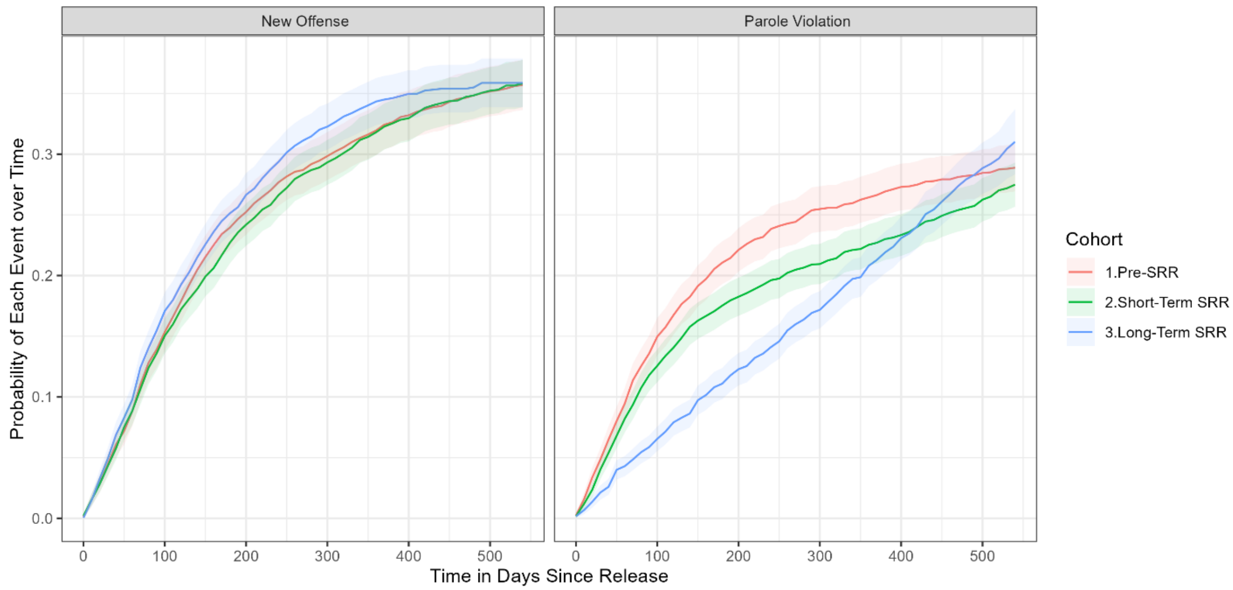
Outcome	Comparison	HR (95% CI)	Coefficient	S.E.	p-value
Parole Violation	Pre - Short	.922 (0.82 – 1.03)	-0.08	0.06	0.160
	Pre - Long	.870 (0.78 – 0.98)	-0.14	0.06	0.016
	Long - Short	1.06 (0.95 – 1.18)	0.06	0.06	0.310
New Offense	Pre - Short	1.02 (0.93 – 1.13)	0.02	0.05	0.670
	Pre - Long	1.04 (0.94 – 1.15)	0.04	0.05	0.460
	Long - Short	.984 (0.89 – 1.08)	-0.02	0.05	0.740

Survival Curves

It is usually difficult to understand what a survival model is indicating based on a table of coefficients alone. To aid interpretation, a graphical representation of survival curves is provided next. In Figure 3, the y-axis shows the probability of event occurrence and represents the proportion (out of 1.0 or 100%) of each cohort who have returned to prison for a parole violation or who have committed a new offense at a given value of time (measured in days, x-axis). In the figure, new offenses and parole violations are in separate panels and cohorts are represented by different colors as outlined in the figure's legend. The solid lines represent individual survival curves for each cohort and the identically colored, shaded bands around the lines reflect the confidence intervals.

Recall from Table 7 that the rate of return for parole violations was slower for the short-term SRR cohort compared to the pre-SRR cohort, but the difference was not significant. In the figure, one can see a small difference between the two survival curves and that small difference is reflected in the p-value in Table 7; that is, although not significant, the p-value is somewhat small (p = .160) and so the two cohorts do not overlap substantially in their survival rates. Nevertheless, because the difference is not significant, the correct interpretation is that the survival rate between the two groups is statistically equivalent.

Figure 3: Probability by Event Type



An interesting pattern is observed for the long-term cohort. Recall from Table 7 that the long-term cohort committed parole violations at a rate 13% slower than the pre-SRR cohort. In the figure, it appears the pre-SRR cohort does return to prison at a faster rate in the period closer to release, but the long-term SRR cohort eventually gains on, and then overtakes, the short-term cohort. This *might* suggest that the effect of SRR is partly to delay parole violations, but not prevent them in the long-term. The difference between the short- and long-term cohorts is also not significant, but, again, part of this is due to the fact that the long-term cohort, despite a slower initial rate of returns, eventually catches and passes the short-term group in probability of committing a parole violation. This is the cause of the non-significant result in this case[8].

In the case of new offenses, the pattern is more easily interpreted because of the fact that the lines reflecting the probability of committing a new offense do not cross, meaning one group does not

[8] It is worth noting that significance tests should be interpreted with caution when, as in the case of parole violations above, lines cross, which indicates a violation of the proportional odds assumption. Typically, in that case, the p-value is not significant because of a loss of statistical power. That does not occur here, but the test has a different interpretation. Rather than interpreting the coefficient as the instantaneous effect related to a predictor (cohort), when lines cross, one should instead interpret the effect as the average effect during the observation period. For references, see: Schober, P., & Vetter, T. R. (2018). Survival analysis and interpretation of time-to-event data. *Anesthesia & Analgesia, 127(3),* 792–798, and Allison P.D. (2010). Survival analysis. In: Hancock G.R., Mueller R.O. (Eds). *The reviewer's guide to quantitative methods in the social sciences* (pp. 413-424). New York, NY: Routledge, Taylor and Francis Group.

overtake another, and the rate for the probability of committing a new offense is more constant. However, one can see the considerable overlap in the survival curves for all cohorts. This is underscored by the results in Table 7; none of the cohorts differ from one another statistically.

A caveat to interpreting the events individually, as above, is that one also needs to consider attrition due to the competing risk sets. For example, though the long-term SRR group commits parole violations at an initially slower rate, part of that effect occurs because they are committing more new offenses (though not at greater rate than other cohorts), which removes them from the risk set for parole violations. For that reason, recidivism owing to both events combined is discussed next.

Event Probabilities

Table 8 below shows the probabilities of committing a parole violation, a new offense, and both outcomes combined as a function of time (in days since release). With the exception of the "Combined" values, the values in the table are reflected in the figure above, but it is sometimes useful to see the values in table form in addition to a figure. To make the table more readable, time is spaced in increments of 90 days, or approximately every three months.

Because the outcomes for individual events were discussed above, the focus here is on the probability of recidivating for any cause (that is, for the two events combined). For expositional purposes, cells for the "Combined" column at day 270, near the middle of the observation period, and day 540, or the end of observation, are **bolded**.

At the end of observation, and conditional on the covariates outlined above, the long-term cohort is slightly more likely to recidivate[9] due to any cause (66.9%) when compared to other cohorts. In the short-term SRR cohort, by the end of observation, and conditional on covariates, 63.3% of parolees are expected to recidivate due to any cause. The pre-SRR cohort falls in the middle of the two, with an expected probability of recidivating due to any cause of 64.6%.

One might elect, instead, to focus on an earlier period. For example, at 270 days, or approximately nine months after release, the pre-SRR cohort (53.1%) is more likely than either the short-term (48.8%) or long-term cohort (47.1%) to recidivate for any cause. This discrepancy between probabilities at the middle and end of the observation period underscores the fact that SRR seemed to slow recidivism due to any cause, but not prevent it. The effect, however, is driven by parole violation rates, which, as shown in the figure above, are notably lower for the long-term SRR cohort, but only early in the observation period.

[9] Because this is a model, and because the outcomes are conditional on covariates, the probabilities are not identical to raw values. A statistical model, in contrast to raw values, provides an estimate of the effect in the population rather than in a specific sample.

Table 8: Event Probabilities at 90 Day Intervals by Cohort

Cohort	Event	Day 0	Day 90	Day 180	Day 270	Day 360	Day 450	Day 540
Parole Violation	Pre-SRR	0.002	0.136	0.211	0.244	0.264	0.279	0.289
	Short-Term SRR	0.002	0.118	0.175	0.205	0.225	0.249	0.275
	Long-Term SRR	0.002	0.059	0.111	0.160	0.208	0.261	0.310
New Offense	Pre-SRR	0.001	0.139	0.239	0.287	0.320	0.343	0.357
	Short-Term SRR	0.002	0.136	0.227	0.283	0.318	0.344	0.358
	Long-Term SRR	0.000	0.155	0.251	0.311	0.343	0.354	0.359
Combined	Pre-SRR	0.004	0.275	0.450	**0.531**	0.584	0.622	**0.646**
	Short-Term SRR	0.004	0.254	0.402	**0.488**	0.543	0.593	**0.633**
	Long-Term SRR	0.002	0.213	0.362	**0.471**	0.551	0.615	**0.669**

Discussion

Needs-to-Case Action Plan (CAP) Alignment

Over the past decade, several studies have examined the quality of service-to-need matching in the juvenile and criminal justice systems (e.g., Luong & Wormith, 2011; Peterson-Badali et al., 2015; Nelson & Vincent, 2018; Drawbridge et al., 2020). Findings from several studies have demonstrated that about half of the samples are receiving the services that they need (e.g., Luong & Wormith, 2011). More recently, Nelson and Vincent (2018) found that a high percentage of youth in their sample had a good service-to-need match. The findings in this report add to the research by examining the quality of service-to-need matching following the implementation of a number of state-level initiatives aimed at reducing recidivism in Utah.

This study revealed some support for adherence to the RNR model when assigning services to parolees. The findings demonstrated that Utah Adult Probation & Parole (AP&P) agents generally followed the risk principle by assigning more services to higher-risk parolees than lower-risk parolees. Higher-risk parolees also had more of their needs met with services compared to lower-risk parolees. While 74.4% of parolees had at least one of their criminogenic needs met, few parolees received services to address more than three criminogenic needs. There are several possible explanations for this finding. It may be that there was a lack of resources during the Covid-19 pandemic, including the lack of certain groups or a pause of face-to-face interventions. It may also suggest that AP&P agents were focusing their efforts to improve one need area, so that it does not become overwhelming for parolees. Research has consistently demonstrated that behavior change is difficult. Additionally, parolees may have received services to address their priority needs before the start of their parole term or prior to the timeframe for these analyses (i.e., July 1, 2020).

AP&P did better in some areas of service-to-need matching than others. In particular, agents did reasonably well in service-to-need matching with respect to alcohol and drug problems and procriminal attitudes/orientation. On the other end, service-to-need matching could be improved in all areas – particularly in the areas of criminal history, leisure and recreation, companions, and antisocial patterns. With the exception of service referrals for alcohol/drug problems and procriminal attitudes/orientation, agents were better at matching services to needs when absent. This can be demonstrated by the significantly higher rates of underprescription when compared to the rates of overprescription. Unfortunately, greater than 88% of parolees who had a need area present other than alcohol/drug problems and procriminal attitudes/orientation were underprescribed services. It is possible that the Covid-19 pandemic contributed to the underprescription of services due to a lack of community-based services offered during this time. It is also important to note that parolees in this sample may have received services to address their needs prior to the start of their parole term or the full implementation date of tracking service-to-need alignment determined by UDC (i.e., July 1, 2020).

The analysis of all CAP events revealed that there was an improvement in service-to-needs matching over time with the exception of a couple of months. There appeared to be a slight overall increase over the 14-month period analyzed in this report. It is possible that this relationship could have been artificially deflated because the initiative to improve service-to-needs matching was implemented prior to July 1, 2020; however, the system to track alignment was not fully implemented until this date.

Recidivism

The long-term SRR cohort, the cohort representing full implementation of SRR initiatives, was associated with a decrease in the rate of recidivism due to parole violations, but only early in the observation period. By the end of the observation period, there were no differences in the cohorts in terms of rates of parole violations. There were no differences at all between the cohorts in terms of rates of recidivism for new offenses. The findings suggest that the primary effect of SRR may have been to delay parole violations.

Conclusions drawn from the recidivism section must be viewed with some caution owing to caveats discussed above and elaborated upon here. First, potential history effects are a threat to any longitudinal design. While the model attempted to balance the cohorts on some covariates statistically associated with recidivism, not all potential confounders could be addressed. Among these are differences in state- and community-level policies that might have impacted the cohorts differently. These variables are not available and could not be controlled in the models presented in this section.

It is worth noting that the pattern observed in Figure 3 for the long-term cohort, with respect to parole violations, is very unusual because it suggests a nearly constant rate of return for parole violations. All other curves in the figure are more typical of what one usually sees in survival curves because, generally, the longer people "survive", the more likely they are to survive given observation time – hence the general pattern of a flattening curve at longer observation periods for the other cohorts. It is worth considering possible causes of this unusual pattern. While there may be other causes of the effect, the Covid-19 pandemic certainly stands out as one in need of consideration.

It is difficult to quantify the effect the pandemic had on both parole violations and new offenses, but the fact that UDC halted, for a period of time, face-to-face meetings and fugitive roundups could have presumably slowed the rate of parole violations for the long-term cohort, the cohort for which the worst of the pandemic overlapped most notably. This may partially explain the pattern observed in Figure 3 above. Similarly, resuming normal operations may partially account for the fact that the long-term cohort accelerated past other cohorts in rate of return for parole violations near the end of the observation period, the period in which normal operations began to resume.

Given that face-to-face contact, some aspects of treatment, and general supervision were notably reduced during the observation period for the long-term cohort, it is also worth considering the potential impact this might have had on recidivism due to new offenses within this cohort. With less community supervision and treatment services relative to other cohorts, one might expect greater recidivism due to new offenses for the cohort, but, as seen above, this did not occur.

It is possible that the SRR initiatives that were implemented in prison, prior to release, had some impact on recidivism once released despite a lack of community supervision and treatment on par with the other cohorts. While this could arguably be dismissed as post hoc speculation given the inability to quantify the pandemic's effect, it is certainly the case that the impact of the pandemic is not negligible, and one must at least consider the genuine possibility that SRR initiatives that occurred prior to release did reduce recidivism for new offenses relative to what it might have been given a lack of community-based services caused by the pandemic.

Some evidence for this hypothesis is found in the initially lower rate of parole violations within the long-term cohort. Because this cohort committed less parole violations initially, they had more availability in the risk set to commit new offenses. In contrast, because the other cohorts committed more parole violations, they had less availability in the risk set to commit as many new offenses. Thus, while the long-term cohort had more availability in the risk set to commit new offenses, they did not do so. This suggests SRR may have reduced (or delayed) new offenses despite the similar rates at which they occurred across cohorts. Whenever competing risks exist, it is always important to evaluate loss of availability across the risk sets for these types of patterns.

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