TECHNICAL SUPPLEMENT

Support for the Journey Home

An Impact Study of the Returning Citizens Stimulus Program

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This supplement contains additional information about the propensity score matching procedure, impact analyses, and sensitivity checks conducted for the Returning Citizens Stimulus impact study.

Data Source

The California Department of Corrections and Rehabilitation (CDCR) provided MDRC with linked administrative datasets with the following information: demographics, incarceration history, in-prison rule violations history, in-prison work assignments, post-release parole violations, and reincarceration data.

Sampling Strategy

The program relied on a network-sampling approach to enrolling participants. To spread the word about the program and how to get involved, CEO and other local reentry organizations used a "snowball" sampling approach driven by their existing referral networks and word-of-mouth referrals of program participants. A smaller subset of participants were referred to RCS by their probation or parole officers, who facilitated a connection with RCS representatives.[1] Thus, nonparticipants were generally people not in the referral networks of local organizations or the personal networks of those knowledgeable about the program. Nonparticipants may also have included people who were informed of the program but were not interested in participating. In addition to the usual risk of bias associated with research and specifically quasi-experimental research, a snowball sampling strategy can increase the risk of sample selection bias. As such, all

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causal estimates in this report should be interpreted with caution; further research is needed to corroborate these findings.

Target of Inference

The target of inference is the average effect of having received at least one cash transfer from the RCS program, an average treatment effect on the treated (ATET) approach.

Propensity Score Matching Process

CDCR provided data on 824 RCS program participants and 8,603 nonparticipants released from prison during the period in which the RCS program was distributing funds. The MDRC team used propensity score matching (PSM) to create comparable research groups out of the pool of RCS participants and nonparticipants. A propensity score is a conditional probability that predicts the likelihood that an individual will participate in a program based on characteristics or factors such as race, gender, or the extent of their prior contact with the criminal legal system. Participants and nonparticipants were assigned propensity scores predicting how likely each would be — based on a set of personal factors — to participate in the RCS program. Participants were then matched to nonparticipants with similar propensity scores to create two groups: the participant group and the comparison group. This process was used to maximize the likelihood that the research groups were substantially similar on observed characteristics.

Note that although propensity score matching is a powerful analytic tool, it can provide an incorrect finding if there are unobserved characteristics or factors (meaning those for which the researchers do not have data) related to program participation and recidivism. Wherever possible, the research team has instituted statistical sensitivity checks to quantify the risk of omitted variable bias. The results of these checks are summarized below in this Technical Supplement.

To create the propensity scores, the analysis team used logistic regression to estimate the relationship between observed characteristics and whether someone participated in RCS. In selecting covariates, the team followed the research literature on propensity score matching, which indicates that covariates known to be related to program participation or the outcomes of interest should be included in the model. The literature further advises that including more covariates than may be necessary is likely not harmful and is preferable to omitting important variables.[2] Therefore, covariates were selected based on findings from past research on criminal legal system involvement for people involved with the justice system.[3] These covariates were:

- Binary gender indicator (male or female)[4]
- Age at release from baseline incarceration[5]

- Race/ethnicity (possible values: Black, White, Hispanic/Latinx, Asian or Pacific Islander, Native American, and other)
- Release county (Los Angeles or Alameda)
- Binary indicator for whether the baseline incarceration is the individual's first incarceration in CDCR facilities
- Controlling offense category for baseline incarceration[6]
- Number of months incarcerated for baseline incarceration
- Binary indicator for whether the person had an additional incarceration within a time frame of
    - 2 years prior to baseline date[7]
    - 5 years prior to baseline date
    - 10 years prior to baseline date
- Number of days incarcerated within a time frame of
    - 2 years prior to baseline date (including baseline incarceration)
    - 5 years prior to baseline date (including baseline incarceration)
    - 10 years prior to baseline date (including baseline incarceration)
- Binary indicator for whether the person had an additional incarceration for a violent crime within a time frame of
    - 2 years prior to baseline date
    - 5 years prior to baseline date
- Binary indicator for whether the person had an additional incarceration for a property crime within a time frame of
    - 2 years prior to baseline date
    - 5 years prior to baseline date
- Number of additional incarcerations for a property crime within the 5 years prior to baseline date

- Binary indicator for whether the person had a parole violation within the 2 years prior to baseline date
- Number of parole violations in the 2 years prior to baseline date

The logistic regressions produced coefficients that represented the estimated relationship between each predictor and the likelihood that a person would participate in RCS. Each person's individual characteristics and factors were then multiplied by these coefficients to create a score between 0 and 1, where a score of 0 meant that the individual was estimated to be completely unlikely to participate in RCS and a score of 1 meant that the individual was estimated to be certain to participate.

The research team matched program participants to nonparticipants with similar propensity scores using one-to-one nearest neighbor matching. The team ran the match without replacement, allowing each person to be matched only once. To ensure that program participants were matched with nonparticipants with a somewhat similar likelihood of program participation, the research team used a caliper of 0.2. Using a caliper of this size prohibits the statistical computing software from matching together two individuals who have propensity scores greater than 0.2 units apart on the 0 to 1 scale. The caliper size was chosen based on recommendations in the literature and established MDRC practice.[8] The matching process produced a 100 percent match rate, meaning that all RCS participants were successfully matched to similar nonparticipants. This resulted in a total analysis sample size of 1,648 people, half of whom were participants and half of whom were comparison group members.

As shown in Table 1 in this supplement, the full unmatched groups of participants and nonparticipants were statistically different on many of the covariates. Table 2 in this supplement shows characteristics of the analysis sample after matching; all but one of the statistically significant differences on observed covariates between the groups were eliminated during the matching process. One or two statistically significant differences are expected even in a random experiment.

Propensity Score Checks

After assigning propensity scores to each participant and nonparticipant, the team performed a series of graphical checks on the scores: a graph of the overlap in propensity scores between the participant and nonparticipant groups (region of common support), a density plot of the slope of the probability distribution, and line graphs of the quantile of probability. See Figure 1 in this supplement for the region of common support graph for the unmatched pool of people eligible for the program, bifurcated by participation status. Participants and nonparticipants had a similar distribution of propensity scores, even before matching. After matching, as Technical Supplement Figure 2 shows, the matched program and comparison units had nearly identical propensity score distributions. The average difference between matched propensity scores is less than 0.0001.

Technical Supplement Table 1. Characteristics of RCS Participants and Nonparticipants

	Participant Group	Comparison Group	Difference	P-Value	
Average age	40.29	37.66	2.62	0.000	***
Gender (%)					
Female	7.28	6.71	0.57	0.530	
Male	92.72	93.29	-0.57	0.530	
Race (%)					
Black	47.57	32.80	14.77	0.000	***
Latinx	37.38	50.96	-13.58	0.000	***
White	11.41	11.54	-0.13	0.908	
Asian or Pacific Islander	0.73	1.09	-0.36	0.329	
Native American, Hawaiian, Alaskan	0.24	0.28	-0.04	0.850	
Other	2.67	3.32	-0.65	0.313	
Release county (%)					
Los Angeles	94.54	93.39	1.15	0.200	
Alameda	5.46	6.61	-1.15	0.200	
Controlling charge category (%)					
Violent	58.62	52.28	6.33	0.001	***
Property	20.15	21.53	-1.38	0.356	
Drug	6.31	7.87	-1.56	0.110	
Public order/other	14.93	18.32	-3.39	0.016	**
Baseline incarceration					
Baseline incarceration is first CDCR incarceration (%)	45.02	44.36	0.67	0.713	
Average length of baseline incarceration (in months)	81.32	48.27	33.05	0.000	***
Two-year criminal legal background measures					
Ever incarcerated (%)	0.73	1.29	-0.56	0.164	
Ever incarcerated for a violent offense (%)	0.00	0.30	-0.30	0.114	
Ever incarcerated for a property offense (%)	0.24	0.34	-0.09	0.651	
Average number of days incarcerated	588.71	512.31	76.40	0.000	***
Ever had a parole violation	4.25	6.64	-2.39	0.008	***
Average number of parole violations	0.10	0.16	-0.06	0.022	**

(continued)

Technical Supplement Table 1 (continued)

	Participant Group	Comparison Group	Difference	P-Value	
Five-year criminal legal background measures					
Ever incarcerated (%)	9.95	15.88	-5.93	0.000	***
Ever incarcerated for a violent offense (%)	2.91	4.91	-1.99	0.010	**
Ever incarcerated for a property offense (%)	3.40	5.08	-1.68	0.033	**
Average number of incarcerations for a property offense	0.04	0.05	-0.02	0.046	**
Average number of days incarcerated	1,145.51	911.16	234.35	0.000	***
Ten-year criminal legal background measures					
Ever incarcerated (%)	24.15	35.13	-10.98	0.000	***
Sample size	824	8,603			

SOURCE: Calculations based on data from the California Department of Justice and the California Department of Corrections and Rehabilitation.

NOTE: Statistical significance levels are indicated as: *** = 1 percent; ** = 5 percent; * = 10 percent.

Matching Sensitivity Checks

To assess the strength of the matching process, the research team used a variety of graphical and statistical sensitivity checks at each stage of the analysis. The team has reported the match rate as a function of the number of matched program units divided by the number of all available program units. One major critique of the PSM method is that it prunes from the sample all participants who cannot be matched within the caliper, introducing bias into the resulting analysis sample. The fact that no program units were lost in the matching process in this study eliminates this particular risk of PSM.

The team used three methods to assess covariate balance: means comparison, logistic regression, and an average standardized difference love plot. First, the team compared the covariate means for the two research groups to ensure that they were substantially similar. Table 2 shows the covariate means for the matched sample, split by research group, confirming that they were, in fact, substantially similar. Second, the team performed a logistic regression on the matched research groups to see if there were any statistically significant differences between them. The regression showed no statistically significant differences between the matched research groups on all covariates.[9] Finally, the team constructed an average standardized difference love plot to quantify and graphically represent the standardized differences between the groups on the various covariates. The team used the cobalt bal.tab() function in R to produce balance statistics based on the program variable (participation in RCS). The team then extracted the standardized difference statistics for

Technical Supplement Table 2. Characteristics of Analysis Sample

	Participant Group	Comparison Group	Difference	P-Value	
Average age	40.29	40.50	-0.21	0.737	
Gender (%)					
Female	7.28	6.80	0.49	0.700	
Male	92.72	93.20	-0.49	0.700	
Race (%)					
Black	47.57	45.51	2.06	0.401	
Latinx	37.38	39.68	-2.31	0.336	
White	11.41	11.89	-0.49	0.759	
Asian or Pacific Islander	0.73	0.73	0.00	1.000	
Native American, Hawaiian, Alaskan	0.24	0.24	0.00	1.000	
Other	2.67	1.94	0.73	0.325	
Release county (%)					
Los Angeles	94.54	95.63	-1.09	0.305	
Alameda	5.46	4.37	1.09	0.305	
Controlling charge category (%)					
Violent	58.62	60.80	-2.18	0.366	
Property	20.15	20.15	0.00	1.000	
Drug	6.31	5.46	0.85	0.464	
Public order/other	14.93	13.59	1.33	0.439	
Baseline incarceration					
Baseline incarceration is first CDCR incarceration (%)	45.02	44.05	0.97	0.692	
Average length of baseline incarceration (in months)	81.32	80.51	0.81	0.874	
Two-year criminal legal background measures					
Ever incarcerated (%)	0.73	0.12	0.61	0.058	*
Ever incarcerated for a violent offense (%)	NA	NA	NA	NA	
Ever incarcerated for a property offense (%)	0.24	0.00	0.24	0.157	
Average number of days incarcerated	588.71	589.31	-0.60	0.952	
Ever had a parole violation	4.25	3.76	0.49	0.616	
Average number of parole violations	0.10	0.09	0.01	0.662	

(continued)

Technical Supplement Table 2 (continued)

	Participant Group	Comparison Group	Difference	P-Value
Five-year criminal legal background measures				
Ever incarcerated (%)	9.95	9.10	0.85	0.557
Ever incarcerated for a violent offense (%)	2.91	2.55	0.36	0.650
Ever incarcerated for a property offense (%)	3.40	3.28	0.12	0.891
Average number of incarcerations for a property offense	0.04	0.03	0.00	0.696
Average number of days incarcerated	1,145.51	1,154.83	-9.31	0.763
Ten-year criminal legal background measures				
Ever incarcerated (%)	24.15	22.57	1.58	0.449
Sample size	824	824		

SOURCE: Calculations based on data from the California Department of Justice and the California Department of Corrections and Rehabilitation.

NOTE: Statistical significance levels are indicated as: *** = 1 percent; ** = 5 percent; * = 10 percent.

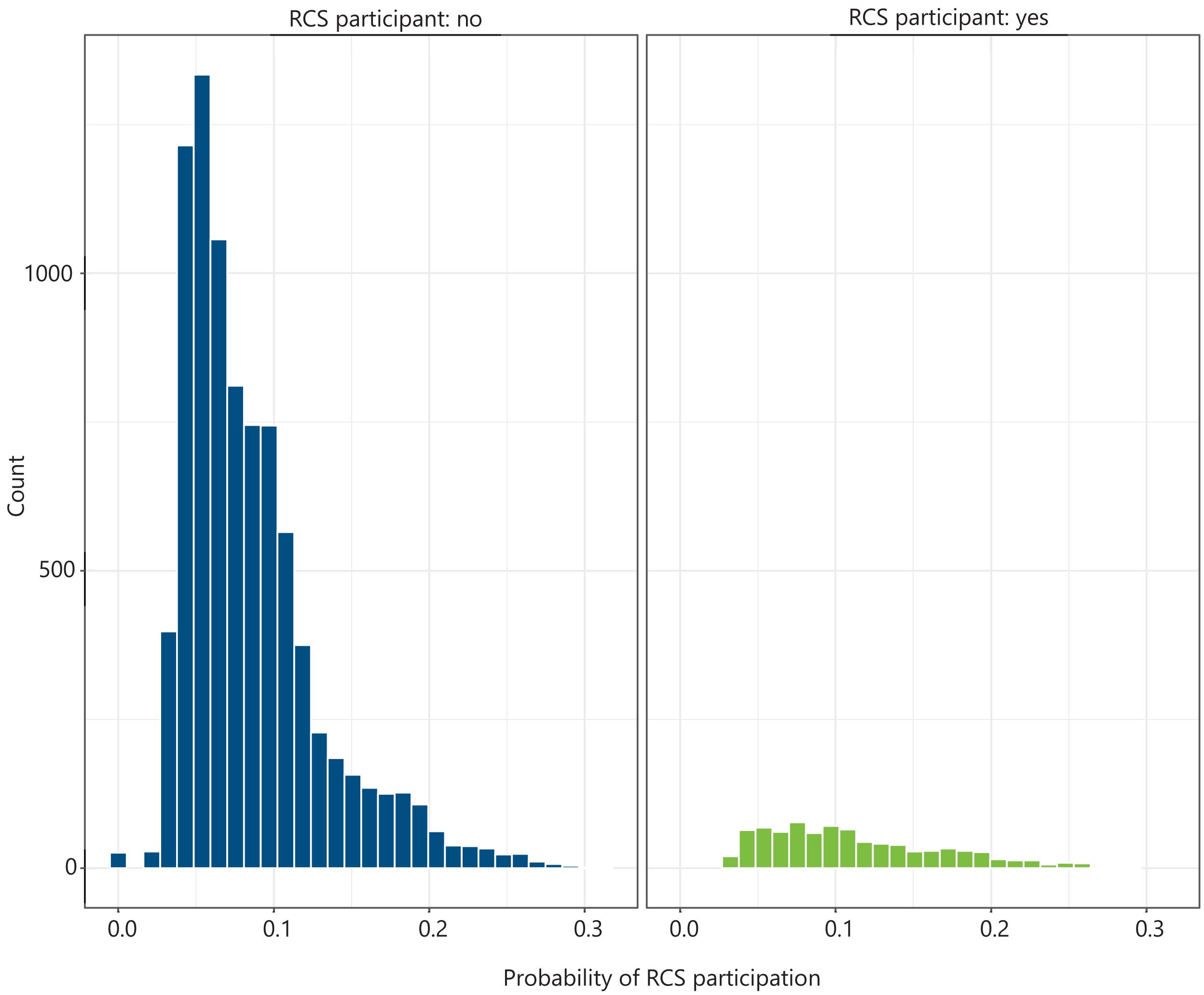
each covariate and plotted them in relation to x = 0. As shown in Figure 3 in this supplement, all the standardized distances fell between –0.03 and 0.03.

Model Sensitivity Checks

To test the strength of the analysis model and prevent overfitting, the team deployed an iterative model-building approach as a sensitivity check. In addition to running the analysis on the model with all the covariates listed above, the team ran a "minimalist" propensity model containing only covariates with the highest predictive power over RCS participation. If the regression output for any of the impacts was significantly different in magnitude or sign across the two models, that would indicate a need to reassess the covariates used in the matching and impact model.

To create the minimalist model, the team needed to assess the relative predictive power of each covariate. To do this, the team ranked each covariate's R-squared value from a single linear regression where participation was the dependent variable and the covariate was the independent variable. The quartiles of the ranked list were then identified. Covariates associated with the values in the fourth quartile (all covariates) were defined as the primary model, and only those in the second quartile were included in the minimalist model. Based on this modified approach, the model tiers tested on the outcomes were:

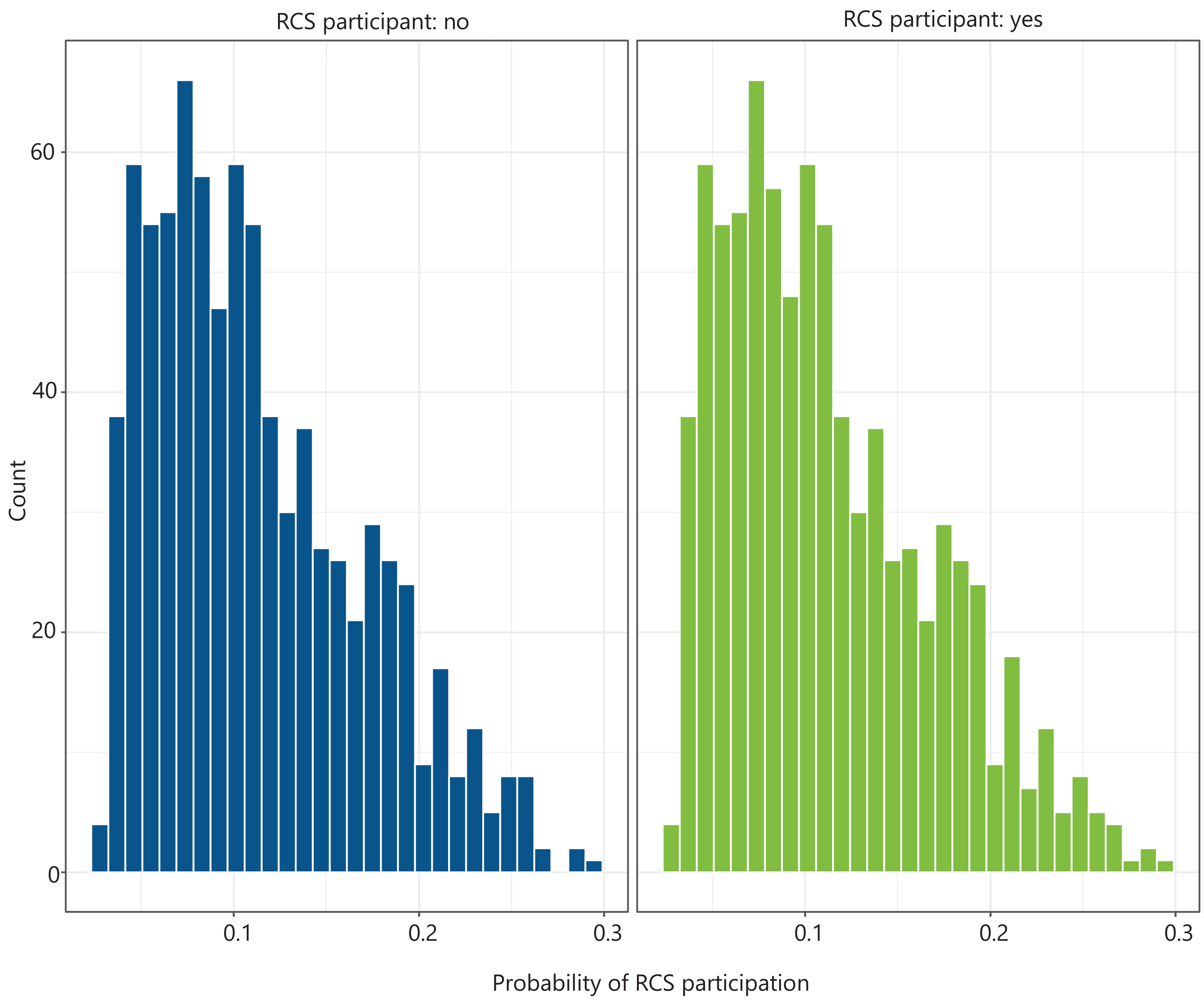
Technical Supplement Figure 1



SOURCE: MDRC analysis of the propensity score distribution before matching.

- Tier one ("minimalist"):
  - Race/ethnicity
  - Release county
  - Indicator for whether the person had an additional incarceration in the 10 years prior to baseline
  - Indicator for whether the person was incarcerated for a property crime in the 5 years prior to baseline
  - Number of days incarcerated in the 5 years prior to baseline
- Tier two ("maximalist"): all covariates

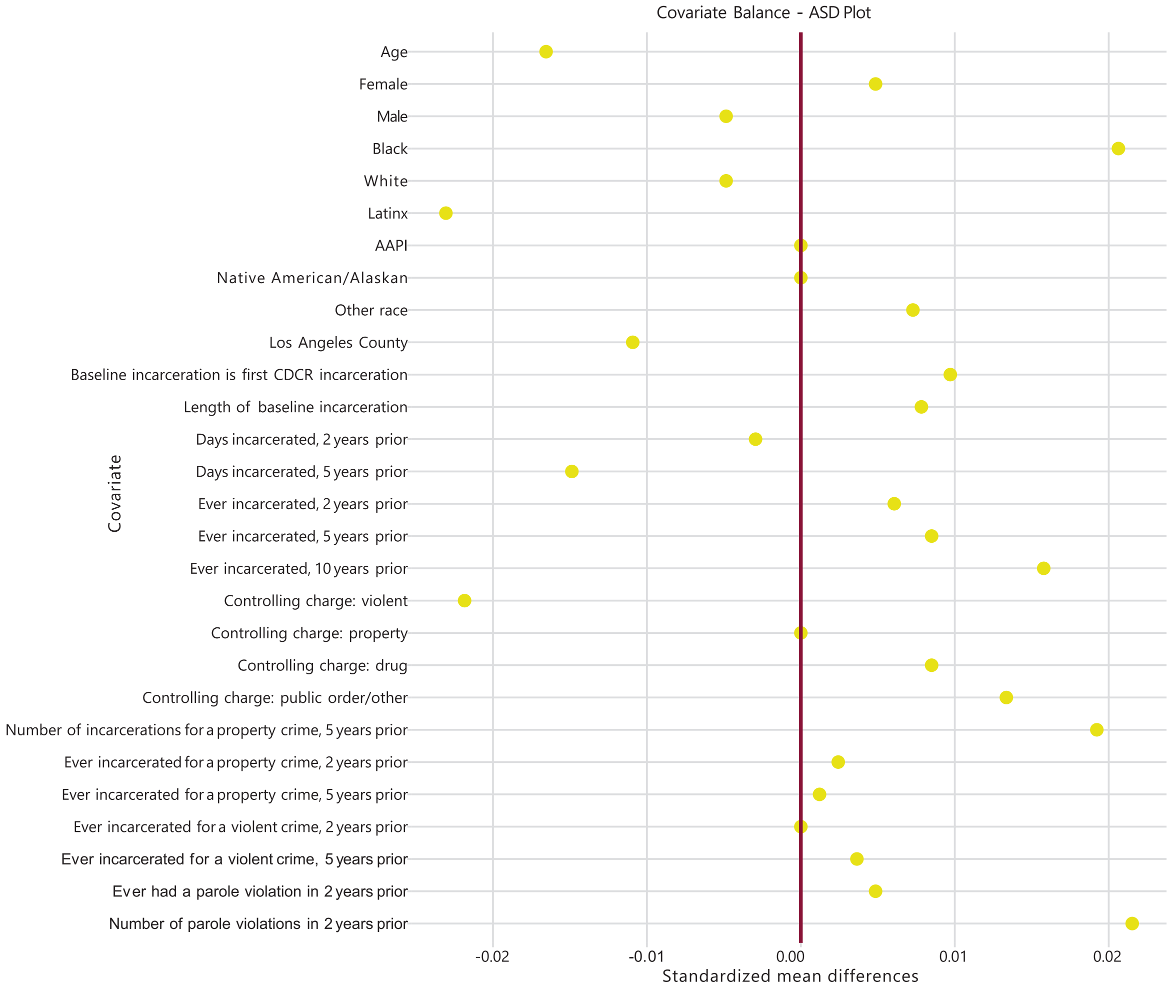
Technical Supplement Figure 2



SOURCE: MDRC analysis of the propensity score distribution after matching.

The tier one model produced similarly balanced research groups on the full set of maximalist-model covariates. However, the model had an F-statistic of 0.25—nearly half that of the tier two model, which had an F-statistic of 0.48. As such, the tier two model is preferable, as it has more explanatory power over the dependent variable of participation in RCS.

Technical Supplement Figure 3



SOURCE: MDRC analysis of the propensity score matching results.

Outcome Sensitivity Checks

The following sensitivity checks were used to evaluate the study outcomes.

Benjamini-Hochberg Procedure

To minimize the false discovery rate, or the likelihood of estimating an erroneous effect, the research team implemented the Benjamini-Hochberg (BH) procedure on all outcomes. Under the adjusted p-values produced by the BH procedure, all 6-month parole violation impacts remained statistically significant at the 0.05 level or better. Among the 12-month measures, the rate of violent parole violations, the rate of general parole violations, and the number of parole violations are all statistically significant at the 0.1 level. The outcome for the number of violent parole violations is statistically significant at the 0.05 level. This provides support for the observation that the program was more effective closer to the time in which participants were actively receiving the stimulus payments. None of the adjusted p-values for the reincarceration outcomes surpassed the 0.1 threshold for significance.

Rosenbaum Bounds

The research team also conducted Rosenbaum bounds tests to assess the validity of the results. These tests are designed to assess the assumption of conditional independence of participation status implicit in propensity score analysis. They do this by determining how strong an effect an unmeasured confounding variable would need to have on participation status to significantly influence the estimated causal effect. Two tests were used for continuous outcome variables: the Wilcoxon signed rank test and the Hodges-Lehmann point estimate test. Two tests were used for binary outcome variables: the Wilcoxon signed rank test and McNemar's test.

Under the logic of Rosenbaum bounds, all four 6-month parole violation outcomes were robust against omitted variable bias, each requiring that an omitted variable influence the likelihood of program participation by 50 percent or more to change the estimated effect. The 12-month parole violation measures were far more susceptible to bias, with the exception of the measure for the number of violent parole violations, which was as robust against unmeasured bias as the 6-month measures. All reincarceration outcomes were susceptible to bias, and therefore additional research is required to determine the validity of these results.

Robustness of Inference to Replacement (RIR)

As an additional assessment of bias, the team used the robustness of inference to replacement (RIR) calculation. This nonparametric case replacement approach quantifies the robustness of inference in terms of the number of observed cases in a given sample that must be replaced with zero-effect cases to change the inference. In other words, the RIR answers the following question: What proportion of the observed data must be replaced with hypothetical data (for which the program effect is zero) to change an inference?[10] For all 6-month parole violation measures, between 25 and 50 percent of the observed data would need to be replaced with a null effect to change the inference. For the 12-month general parole violation measures, only between 5 and 10 percent of the observed data would need to be replaced to change the inference. As with the Rosenbaum bounds tests, the measure for the number of violent parole violations in the 12-month follow-up is more robust. For this inference to be nullified, about 30 percent of the data would need to be replaced with zero-effect data. RIR could not be performed on the reincarceration outcomes because an underlying assumption of this test is that the p-value is below the 0.05 threshold, not at or above it.

Subgroup Analyses

Additional information about the subgroup analyses is presented below.

Age

The research team ran a subgroup analysis on the parole violation outcomes by age band. The groupings were 18 to 24, 25 to 34, 35 to 49, and 50 and above. Technical Supplement Table 3 shows the results of this analysis, with the final column indicating whether there was a significant difference across the age groups, as indicated by the H-statistic. Only two impacts had a statistically significant difference across the age groups: the numbers of parole violations for a violent offense 12 and 18 months after release. The subgroup analysis shows that the greatest effect magnitude on these measures occurred for the youngest age group — those ages 18 to 24 — and for the group aged 35 to 49. Given the low number of significant impacts and the small sample sizes of each group, it is possible that these findings are due to chance. However, given the consistency of significance for the same measure over time, it is also possible that the program was more effective at reducing violent parole violations for members of the 18-to-24 and 35-to-49 age groups, compared with members of other age groups.

Race/Ethnicity

Table 4 in this supplement shows the results from a subgroup analysis based on a combined race/ethnicity variable. To meet the threshold for inclusion, a race/ethnicity value had to have a sample size exceeding 20 times the number of covariates in the regression model. The model for this analysis has 28 covariates (including several binary indicators for categorical fields), meaning that a race/ethnicity value had to have a sample size of at least 560 to be included as a separate group in the subgroup analysis. Only two race/ethnicity values met this criterion: Black and Latinx/Hispanic. All other racial categories are collapsed under the group “Other.” Overall, the subgroup analysis is unremarkable. However, two impacts had significant differences across the subgroups: the rate and the number of parole violations for a violent offense at the 12-month follow-up. For these measures, participants in the Black subgroup benefitted more substantially from the RCS program than other racial/ethnic groups.

Technical Supplement Table 3. Age Subgroup Analysis

	18-24			25-34		
Outcome	**Comparison Group**	**Participant Group**	**Difference**	**Comparison Group**	**Participant Group**	**Difference**
6-month outcomes						
Ever had a parole violation (%)	22.73	15.09	-7.64	15.08	10.04	-5.0
Number of parole violations	0.29	0.24	-0.05	0.21	0.14	-0.1
Ever had a parole violation for a violent offense (%)	9.62	4.41	-5.21	2.65	1.18	-1.5
Number of parole violations for a violent offense	0.10	0.04	-0.05	0.03	0.01	0.0
12-month outcomes						
Ever had a parole violation (%)	37.38	33.98	-3.40	25.37	22.11	-3.3
Number of parole violations	0.76	0.56	-0.20	0.46	0.41	-0.1
Ever had a parole violation for a violent offense (%)	18.48	12.34	-6.14	6.40	5.67	-0.7
Number of parole violations for a violent offense	0.24	0.12	-0.12	0.07	0.06	0.0
Ever reincarcerated (%)	2.36	6.00	3.64	3.01	0.77	-2.2
18-month outcomes						
Ever had a parole violation (%)	39.09	35.06	-4.03	26.81	25.46	-1.4
Number of parole violations	1.12	0.69	-0.44	0.62	0.55	-0.1
Ever had a parole violation for a violent offense (%)	20.08	14.92	-5.15	7.33	9.18	1.9
Number of parole violations for a violent offense	0.28	0.14	-0.15	0.09	0.10	0.0
Ever reincarcerated (%)	9.82	8.37	-1.44	5.95	3.70	-2.3
24-month outcomes						
Ever reincarcerated (%)	15.94	13.45	-2.49	10.91	8.08	-2.8
30-month outcomes						
Ever reincarcerated (%)	21.15	16.64	-4.51	14.88	11.49	-3.39
Sample size	71	72		270	242	

(continued)

Technical Supplement Table 3 (continued)

Outcome	35-49 Comparison Group	35-49 Participant Group	35-49 Difference	50+ Comparison Group	50+ Participant Group	50+ Difference	H-Stat. Sig.
6-month outcomes							
Ever had a parole violation (%)	11.38	4.68	-6.70	15.93	8.85	-7.08	
Number of parole violations	0.19	0.09	-0.09	0.25	0.14	-0.11	
Ever had a parole violation for a violent offense (%)	3.12	0.50	-2.63	0.52	-0.04	-0.57	
Number of parole violations for a violent offense	0.04	0.00	0.03	0.01	0.00	-0.01	
12-month outcomes							
Ever had a parole violation (%)	19.99	14.23	-5.76	23.25	21.70	-1.56	
Number of parole violations	0.45	0.27	-0.18	0.54	0.40	-0.14	
Ever had a parole violation for a violent offense (%)	6.09	1.47	-4.62	1.46	0.47	-1.00	
Number of parole violations for a violent offense	0.08	0.02	-0.06	0.01	0.00	-0.01	†
Ever reincarcerated (%)	1.50	0.64	-0.87	0.37	0.61	0.25	
18-month outcomes							
Ever had a parole violation (%)	21.75	17.66	-4.09	24.65	25.24	0.60	
Number of parole violations	0.64	0.43	-0.20	0.66	0.60	-0.06	
Ever had a parole violation for a violent offense (%)	7.51	2.85	-4.65	1.41	1.02	-0.39	
Number of parole violations for a violent offense	0.09	0.03	-0.06	0.01	0.01	0.00	††
Ever reincarcerated (%)	5.30	2.53	-2.77	1.54	1.39	-0.16	
24-month outcomes							
Ever reincarcerated (%)	7.68	5.38	-2.29	3.78	2.55	-1.244	
30-month outcomes							
Ever reincarcerated (%)	9.79	7.14	-2.65	3.87	3.96	0.08	
Sample size	273	298		209	200		

SOURCE: Calculations based on data from the California Department of Justice and the California Department of Corrections and Rehabilitation.

NOTE: For the H-statistic significance , † = 10 percent, †† = 5 percent, and ††† = 1 percent.

Technical Supplement Table 4. Race/Ethnicity Subgroup Analysis

	Black			Latinx/Hispanic			Other			
	Participant Group	Comparison Group	Difference	Participant Group	Comparison Group	Difference	Participant Group	Comparison Group	Difference	H-Stat. Sig.
6-month outcomes										
Ever had a parole violation (%)	10.23	18.32	-8.08	7.24	10.11	-2.87	7.14	13.29	-6.15	
Number of parole violations	0.17	0.27	-0.10	0.11	0.16	-0.06	0.12	0.20	-0.09	
Ever had a parole violation for a violent offense (%)	0.54	4.52	-3.98	2.04	1.78	0.27				
Number of parole violations for a violent offense	0.01	0.05	-0.04	0.02	0.02	0.00				
12-month outcomes										
Ever had a parole violation (%)	22.03	28.33	-6.31	18.90	19.18	-0.28	20.23	21.41	-1.18	
Number of parole violations	0.41	0.63	-0.23	0.36	0.36	0.00	0.37	0.41	-0.04	
Ever had a parole violation for a violent offense (%)	4.19	8.78	-4.59	4.11	4.76	-0.65	-0.83	0.0	0.85	††
Number of parole violations for a violent offense	0.04	0.11	-0.06	0.04	0.06	-0.02	0.01	0.00	0.01	†††
Ever reincarcerated (%)	0.76	1.35	-0.59	1.64	1.85	-0.21	1.36	2.73	-1.38	
18-month outcomes										
Ever had a parole violation (%)	25.09	30.25	-5.16	21.94	20.65	1.28	24.30	22.22	2.07	
Number of parole violations	0.59	0.83	-0.24	0.50	0.52	-0.01	0.56	0.51	0.04	
Ever had a parole violation for a violent offense (%)	6.57	9.53	-2.95	5.74	5.08	0.66	2.64	2.25	0.39	
Number of parole violations for a violent offense	0.07	0.12	-0.05	0.06	0.06	0.00	0.03	0.02	0.01	
Ever reincarcerated (%)	1.80	3.22	-1.41	4.90	6.78	-1.88	3.34	4.83	-1.48	

(continued)

Technical Supplement Table 4 (continued)

	Black			Latinx/Hispanic			Other			
	Participant Group	Comparison Group	Difference	Participant Group	Comparison Group	Difference	Participant Group	Comparison Group	Difference	H-Stat. Sig.
24-month outcomes										
Ever reincarcerated (%)	5.77	6.34	-0.57	7.58	11.32	-3.74	5.14	6.29	-1.15	
30-month outcomes										
Ever reincarcerated (%)	7.75	8.85	-1.10	10.42	14.50	-4.08	7.07	6.81	0.26	
Sample size	386	374		303	327		123	122		

SOURCE: Calculations based on data from the California Department of Justice and the California Department of Corrections and Rehabilitation.

NOTE: For the H-statistic significance , † = 10 percent, †† = 5 percent, and ††† = 1 percent.

Notes and References

1 Ivonne Garcia, Margaret Hennessy, Erin J. Valentine, Jed Teres, and Rachel Sander, *Paving the Way Home: An Evaluation of the Returning Citizens Stimulus Program* (MDRC, 2021, website: https://www.mdrc.org/sites/default/files/2021_RCS_Evaluation_Report.pdf).

2 See Elizabeth A. Stuart, "Matching Methods for Causal Interference: A Review and a Look Forward," *Statistical Science* 25, 1 (2010); Shenyang Guo, Mark Fraser, and Qi Chen, "Propensity Score Analysis: Recent Debate and Discussion," *Journal of the Society for Social Work and Research* 11, 3 (2020): 463–482.

3 For instance, a meta-analysis conducted by Goodley, Pearson, and Morris (2022) found that prior incarceration, prior convictions, prior arrests, a history of mental illness and being male were consistently associated with recidivism among adults convicted and sentenced to custody. This meta-analysis also found being Black to be a predictor, a finding that the meta-analysis authors attribute to institutional racism in law enforcement and the judicial system.

A meta-analysis by Bechtel, Lowenkamp, and Holsinger (2011) found that age, jail incarcerations, prior convictions, prior felonies, and prior misdemeanors were all predictive of re-arrest among people awaiting trial. In one of the few studies that exclusively focused on people released from jails, Sheeran (2020) found that gender, race, ethnicity, age at release, criminal record, risk score, and time served significantly influenced an individual's likelihood of receiving a new charge, conviction, or incarceration term within three years after release. Lastly, a study by Lebenbaum, Kouyoumdjian, Huang, and Kurdyak (2024) found that among individuals released from provincial corrections institutes in Ontario, Canada, use of mental health services prior to incarceration was associated with higher rates of recidivism, higher rates of hospitalization, and lower rates of outpatient care.

See Gary Goodley, Dominic Pearson, and Paul Morris, "Predictors of Recidivism Following Release from Custody: A Meta-Analysis," Psychology, Crime & Law 28, 7 (2022): 703–729; Kristin Bechtel, Christopher T. Lowenkamp, and Alex Holsinger, *Identifying the Predictors of Pretrial Failure: A Meta-Analysis* (Administrative Office of the United States Courts, 2011); Alyssa Sheeran, "Examining the Influence of Individual and Neighborhood Characteristics on Jail Recidivism" (master's thesis, University of Wisconsin-Milwaukee, 2020, https://dc.uwm.edu/etd/2422/); and Michael Lebenbaum, Fiona Kouyoumdjian, Anjie Huang, and Paul Kurdyak, "The Association Between Prior Mental Health Service Utilization and Risk of Recidivism Among Incarcerated Ontario Residents," *Canadian Journal of Psychiatry* 69, 1 (2024): 21–32.

4 The demographic data provided to MDRC by CDCR contained only binary information on gender.

5 The baseline date for all people in the sample was the release date from their earliest incarceration during the study period (starting January 2020). As such, the baseline incarceration refers to the incarceration stay from which the baseline date is derived: the earliest incarceration the person had within the study period.

6 A controlling offense is the crime for which the sentencing court enacted the longest term of imprisonment for the person convicted. For example, if a person were charged with both theft and vandalism and sentenced to four and three months in prison respectively, the controlling charge would be the one with the longer, four-month sentence: theft. Categories for controlling offenses are as follows: violent, property, drug, and public order/other.

7 Unless otherwise indicated, all incarceration metrics exclude study members' baseline incarceration from the calculation of the metric. For example, this metric captures whether a person was incarcerated an additional time during the two years prior to baseline, not counting the incarceration that qualified them for the RCS program.

8 Peter C. Austin, "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies," *Multivariate Behavioral Research* 46, 3 (2011): 399–424; Paul R. Rosenbaum and Donald B. Rubin, "Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score," *The American Statistician* 39, 1 (1985): 33–38.

9 Note that Table 2 in this supplement shows one covariate with statistically different values across the research groups as opposed to zero covariates with such differences. This table used t-tests to assess significance whereas the method used in this sensitivity check was logistical regression, which accounts for this minor difference.

10 Further details can be found in Qinyun Lin, Spiro Maroulis, Joshua Rosenberg, Kenneth Frank, Ran Xu, Anna Mueller, and Thomas Dietz, "Robustness of Inference to Replacement using the konfound R Package," (DOI: 10.13140/RG.2.2.29372.72329), 2022).

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