The Impact of Prison Programming on Recidivism

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Abstract

Prison programming is expensive. From 2009-2011, Iowa spent more than $24 million on prison programming. Some of the programs typically offered in prisons are specifically designed to reduce recidivism while others, such as job training, may reduce recidivism indirectly. Unfortunately, understanding whether programming is effective at reducing recidivism is complicated by prisoners' ability to select into program participation and completion. This paper uses an innovative method to estimate program impacts. Specifically, the sample is limited to prisoners eligible for each program. The sample is further restricted to only those prisoners that either participated in the program or did not participate due to factors beyond their control. Among this sample, nearest neighbor matching is used to evaluate the impact of 16 prison program categories on recidivism. No prison program consistently improved recidivism outcomes in Iowa during the period of analysis.

Keywords: Reenty, Programming, Recidivism, Prison

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1 Introduction

Reentry and Reintegration programs make up a significant part of state corrections budgets. Iowa, for example, spent an estimated $24 million on prison programming between 2009 and 2011 just to service the needs of prisoners released during that period. Some of these programs are specifically designed to reduce recidivism while others, such as job training and education, may reduce recidivism indirectly. Despite the significant expense, it is still not clear that these programs can reduce recidivism rates among participants. Iowa programming is of particular interest in part because Iowa's recidivism rate of 30% is less than half of the national average (Durose et al., 2014).[1] If the programs offered in Iowa are a driving force behind their relatively successful rehabilitation efforts, other states may be able to replicate the Iowa model. This research evaluates whether participation in and/or successful completion of any of 16 distinct program categories reduce recidivism. To the extent that significant differences in the effectiveness of individual programs exist, the research will allow recommendations on which programs are providing the most benefit and thus merit the most funding.

Some evidence has suggested that in-prison programming can meaningfully improve prisoner outcomes upon release (Aos et al., 2006). Unfortunately, despite a large literature considering what works in reentry programming, it has not been convincingly established that the benefits attributed to these programs are caused by them. Some studies have even found that participation in certain programs significantly increases recidivism (Wilson & Davis, 2006). The primary challenge in this literature is the underlying differences between prisoners that actively participate in and successfully complete treatment and those that

[1] The cause of Iowa's exemplary recidivism rates are unclear. One possibility is that many of Iowa's would be recidivists are simply moving to other states and committing crimes there. According to Durose et al. (2015), 13.3% of individuals released from Iowa prisons were arrested in another state within three years. This rate was fifth highest among the 30 states in the sample. Moreover, Iowa continues to use parole widely as opposed to adopting truth-in-sentencing laws. Kuziemko (2012) shows that parole boards are efficient in reducing recidivism rates substantially relative to fixed-sentence regimes.

do not. Even after controlling for observable differences, there is a strong potential that program participants are different on unobservable margins. For example, prisoners more motivated to avoid future incarceration may also be more likely to actively participate and succeed in a variety of prison programs.

In order to account for the potential differences between participants and non-participants, a nearest neighbor matching model among prisoners eligible for each program type is employed. The key innovation here is in the selection of the control group. Instead of finding a nearest neighbor among all untreated prisoners, the potential control group is restricted to prisoners who were eligible to participate in a given program, but did not. Importantly, the reason that each prisoner did not participate is reported in the data. This allows for the exclusion of any prisoners who do not participate by choice. Instead, the control group is comprised of prisoners eligible for a given program, but who did not participate due to constraints outside their control. Examples of these constraints include residing in a facility that does not offer a particular program, the program ending after the prisoner is scheduled to be released, or the program simply not having room for additional people. The central assumption is that among the prisoners included in each regression, program participation is random conditional on the set of observables described. This is plausible given that the reasons for not participating in a program are exogenous to the prisoner and are a function of the natural churn of prisoners through facilities, budget constraints, and prisoner release dates relative to program dates.

The results show that no program offered by the Iowa Department of Corrections (IDOC) significantly reduces recidivism rates. If anything, a few programs appear to increase recidivism. These results hold for both program participation relative to non-participants and successful completers relative to those that do not complete a program they had begun. There is also no effect when restricting the sample to those prisoners identified as most likely to recidivate.

Despite the lack of significant recidivism reduction from programming, it is possible that continued funding of some or all of these programs can still be justified. For example, successful completion of job training programs may send an important signal to potential employers (Bushway & Apel, 2012). Moreover, internal research performed by the Iowa Department of Corrections considered benefits to both taxpayers and crime victims and concluded that the vast many of the programs they offer yielded benefits greater than their costs (IDOC, 2012). Rather than a simplistic focus on recidivism outcomes, policy makers should focus on the total benefits available from each program they offer.

The remainder of this paper proceeds as follows. Section 2 discusses the prior literature in this area and describes the unique contributions of this research. Section 3 presents the methodology used including a discussion of the data and empirical model employed. The findings are presented in Section 4 while Section 5 describes limitations of the research and identifies potential areas for future work. Section 6 concludes.

2 Literature Review

A number of articles have considered the impact of prison programming on recidivism. Unfortunately, this "what works" literature has found mixed results that seem to depend on both institutional setting and the method of analysis employed. One explanation for the variation is that prison programs are just one part of the larger reentry process and the impact of prison programs are influenced by a multitude of other factors (Petersilia, 2004). Another possibility is that the literature has suffered from difficulty in finding a truly similar comparison group with which to compare treated prisoners (Martinson, 1974). Despite this concern, Martinson (1974) concluded that educational and vocational programs do not reduce recidivism rates. Subsequent studies have challenged this conclusion. Specifically, Gendreau & Ross (1979) argued that programs adhering to a specific set of principles could be effective in reducing recidivism and later studies confirmed this finding and further refined the program aspects that were most beneficial (Andrews et al., 1990; Cullen & Gendreau, 2000).

Much of the evidence supporting prison programming as an effective tool comes from large scale meta-analyses of the programming literature (Petersilia, 2004). Unfortunately, these meta-analyses often rely on questionable underlying results. For example, Seiter & Kadela (2003) found only 19 articles that included a comparison group. Even among this group, prison programming was often not randomly assigned meaning that differences between the treatment and control groups, regardless of treatment, were likely.

More recently, researchers have tried to experimentally test the impact of prison programs explicitly designed to follow the principles laid out in Gendreau & Ross (1979). Unfortunately, the results of these interventions have been mixed with some results suggesting moderate improvements while others have found that programming may actually increase the probability of recidivism (Bouffard & Bergseth, 2008; Wilson & Davis, 2006). These results have led to a new focus in the literature on the importance of the characteristics of the individuals, rather than the programs, in determining outcomes. Specifically, Bahr et al. (2010) found that individuals that selected into substance abuse classes tended to spend more time enjoying themselves with friends. This in turn helped these individuals avoid drugs upon release. Evans et al. (2012) found that parolees and probationers benefitted from different types of treatment further solidifying the importance of matching treatment type to individual needs. The value of individually matching prisoners to programs was further confirmed in Gill & Wilson (2016).

The emerging consensus that prisoner-program matching is a key to reducing recidivsm is compelling, but also raises the lingering question of the extent to which fundamental differences between prisoners, and not treatment, are the real cause of differences in prisoner outcomes. Of the above studies, only Gill & Wilson (2016) uses propensity score matching to attempt to find the best possible comparison group. Even this, however, fails to control for the unobservable differences that likely exist between prisoners. This research attempts move another step closer to comparing treated prisoners to control group prisoners that would have identical outcomes in the absence of treatment.

3 Methodolgy

The Iowa Department of Corrections offers a wide variety of programs to prisoners. These programs are organized into 16 board categories; Anger Management, Cognitive Treatment, Domestic Abuse Treatment, Education, Employment Services, Family Treatment, Job Training, Life Skills, Mental Health Treatment, Moderate Intensity Family Violence Prevention Program (MIFVPP), Sex Offender Treatment, Substance Abuse Care, Substance Abuse Treatment, and Victim Treatment. All prisoners are classified as either eligible or not eligible for each program offered. For each program, prisoners may be deemed eligible or ineligible to participate based on a number of characteristics. Among prisoners deemed eligible, some fraction will participate and a subset of participants will successfully complete it. Eligibility is determined by counselors that work with prisoners in each facility and is based on prisoner needs as well as security and privilege levels. Conditional on being eligible, counselor's determine which prisoners will be given the first opportunity to enroll in each program. This ordering is based on a number of factors including available space, time until release, facility moves, disciplinary sanctions, etc. For most programs, prisoners also have the option to refuse enrollment.[2] The average successfully completed program lasted 73 days with about 10% of programs lasting 10 days or less and 10% lasting 134 days or more.

Conditional on enrollment, prisoner success is defined as completion of the program. When programs are not successfully completed, the cause is recorded. For both non-participation and program failure, these causes are placed into two broad categories, outside of prisoner control and within prisoner control. For example, the most common reason for not successfully completing a program is "Transferred to a Different Location" which is

[2]The discretion allowed counselors in program assignment necessarily creates some subjectivity in which prisoners are treated. To the extent that counselors are able to identify those prisoners most likely to be positively affected by a given program, this subjectivity should bias the results towards finding that programming is more effective at reducing recidivism.

categorized as outside of the prisoner's control while the second most common reason, "Non-compliant/Behavioral Issues" clearly qualifies as within a prisoner's control. Table A1 in the Appendix displays all listed reasons for non-completion and indicates to which category the reason was assigned.

Every incoming prisoner is assigned an LSI-R score between 0 and 100. Prisoners are then categorized into one of 5 risk levels based on this score. One indication that these categorizations are accurately measuring recidivism risk can be seen in Table A2 in the Appendix which details the how frequently prisoners in each group recidivated. As expected, prisoners in higher LSI-R categories recidivate at much higher rates than prisoners in low LSI-R categories.[3]

3.1 Program Category Descriptions

While many of the program categories are self explanatory, some are not. In this section, each program category is described and details are provided about what makes a person eligible for programs in that category. The average length of programs in each category, along with the average duration of programs in that category and a brief explanation of the characteristics that would make an individual eligible for each program is provided below.

3.2 Data

The data for this project come from the Iowa Department of Corrections. The data include detailed information about the universe of individuals released from an Iowa prison during the three year period between January 1, 2009 and December 31, 2011. For each prisoner, the data record whether they were eligible for, participated in, and/or successfully completed at least one of the programs in each program category during their incarceration. These binary variables are then used as the key independent variables in the analysis. In addition, the

[3]For a full description of LSI-R scores and their effectiveness at predicting recidivism see Duwe & Rocque (2016).

Program Category	Length	Eligibility
Anger Management	79	Based on counselor discretion or mandated in sentencing
Cognitive Treatment	75	Based on counselor discretion or mandated in sentencing
Domestic Abuse Treatment	91	Based primarily on crime committed
Education	130	Most prisoners eligible, participation based on individual interest and available spots
Employment Services	33	Based on counselor discretion or mandated in sentencing
Family Treatment	57	Based on counselor discretion or mandated in sentencing
Job Training	78	Prisoners without a misconduct are eligible, participation based on individual interest and available spots
Life Skills	28	Most prisoners eligible, participation based on individual interest and available spots
Mental Health Treatment	359	Based on counselor discretion or mandated in sentencing
MIFVPP (Moderate Intensity Family Violence Prevention Program)	92	Based on counselor discretion or mandated in sentencing
Moving On (Domestic Abuse Treatment for Female Prisoners)	79	Based on counselor discretion or mandated in sentencing
Reentry Treatment	33	Based on counselor discretion or mandated in sentencing
Sex Offender Treatment	82	Based primarily on crime committed
Substance Abuse Care	61	Based primarily on crime committed
Substance Abuse Treatment	124	Based primarily on crime committed
Victim Treatment	91	Based on counselor discretion or mandated in sentencing

data include an indicator for whether the individual recidivated within three years of their release.[4] This serves as the dependent variable throughout the analysis.

From an initial sample of more than 12,000 prisoners, any prisoners that either did not participate in or failed a program due to factors within their control are removed. For example, any prisoner refusing to actively participate in one or more programs is excluded from this analysis. This restriction drops 1,604 observations or 13% of the sample. The justification for this exclusion is that these prisoners are systematically different from program participants and completers meaning that any differences in recidivism rates cannot be attributed to the program itself. The unfortunate cost of this exclusion is that, for many

[4]Recent research has documented the varied definitions used for recidivism and how they can dramatically influence results (Rydberg & Grommon, 2016). In this paper, recidivism is defined as a prisoner being released from and returning to incarceration within a three year period. The reason for returning to incarceration could be either a new crime conviction or a technical violation (eg. parole violation). Results for total and new crime recidivism are presented separately.

programs, few prisoners remain in the control group.

Within each program the analysis is further restricted to prisoners coded as eligible for that program. This ensures that all prisoners being evaluated are as similar as possible on both observable and unobservable characteristics. For example, in order to be eligible for Anger Management programming, prisoners must have some sort of anger issue. Anger issues are not directly observable in the data, but may contribute substantially to recidivism probability upon release. Thus, by confining the analysis to prisoners with identified anger issues, the likelihood that any effects are the result of the program itself rather than underlying differences between prisoners is dramatically increased. Unfortunately, this restriction comes with a cost. Specifically, the number of observations available vary widely based on how frequently prisoners are categorized as eligible for the program category being studied.

Table 1 shows the average characteristics of prisoners in the sample. Notably, recidivism rates are much lower in Iowa than the national average with only 31% of prisoners recidivating and only 20% convicted of new crimes. This rate is particularly surprising given that 52% of the sample has recidivated previously. On the other hand, the average age at release is 36. The low recidivism rate may thus in part be driven by the well documented decreases in crime that occur as individuals age (Farrington, 1986). Iowa prisoners are also much more likely to be white and somewhat more likely to be female than national averages (Carson & Anderson, 2016).

3.3 Variables

The dependent variable measures whether the prisoner in question returned to incarceration within three years of their release. In some cases, the cause of this return is that the prisoner simply violated the terms of their parole. In all other cases, the individual recidivates by committing a new crime. In addition to considering total recidivism, the findings section also presents results which only consider an individual to have recidivated if they commit a new crime after release.

The key independent variables indicate whether each inmate was eligible for, participated in, and successfully completed any program falling into each program category during their incarceration. There are three binary variables for each program category. The first records whether the individual was eligible to participate in the program. Rather than appearing in any specification, this variable is used as a screen to eliminate any prisoners not eligible for the indicated program from consideration. The second variable indicates whether eligible prisoners participated in the indicated program. Finally, the third variable indicates whether each prisoner that participated in the indicated program successfully completed it.

I also employ a number of control variables. Specifically;

Variable	Description
LSI-R Score	Estimator used to predict how likely a prisoner is to recidivate within one year of release
Male	Binary indicator of whether the individual is male
Dependents	Number of dependents
Total Crimes	Total number of crimes committed prior to current incarceration
Violent Crimes	Number of violent crimes committed prior to current incarceration
Prior Recidivist	Binary indicator of whether the individual had previously recidivated
Race/Ethnicity	Race and ethnicity of the individual (white, black, Hispanic, or other)
Security Level	Security level of the facility in which the individual spent the most time
Cell Moves	Number of times the individual changed cells
Age	Age at time of release
Misconducts	Average number of misconducts committed per day of incarceration
Visits	Average number of visits received per day of incarceration
Days Incarcerated	Total days incarcerated
Days Probation	Total days on probation or parole
Drug Crime	Binary indicator of whether the individual was convicted of a drug crime
Property Crime	Binary indicator of whether the individual was convicted of a property crime
Violent Crime	Binary indicator of whether the individual was convicted of a violent crime
Public Order Crime	Binary indicator of whether the individual was convicted of a public order crime
Other Crime	Binary indicator of whether the individual was convicted of any crimes not falling into the other categories
Year of Release	The year in which the prisoner was released

3.4 Empirical Model

Restricting the data as described in Section 3 should help make prisoners more similar on unobservable characteristics, but they still may be quite different on observable characteristics such as age, race, and gender, all of which have been shown to be correlated with recidivism (Schmidt & Witte, 1989). To account for these differences, a propensity score matching technique similar to Rosenbaum & Rubin (1983) is employed to estimate change in recidivism, Δ^R, as the average differences between each treated prisoner and an untreated prisoner that most closely matches the treated prisoner's characteristics. Specifically:

$$\Delta^R = \frac{1}{n_1} \sum_{i \epsilon D_i = 1} \left[Y_{1i} - Y_{0j} \right] \tag{1}$$

Where Y_{1i} is the recidivism outcome of treated prisoner i, Y_{0j} is the recidivism outcome for untreated prisoner j. Importantly, prisoner j is the nearest neighbor based on observable characteristics of prisoner i. In order to make the most of the limited available observations, each control group prisoner is allowed to match with multiple treatment group prisoners. Analytical standard errors are calculated as described in Abadie & Imbens (2006).[5]

To the extent that reasonable matches can be created for each treated prisoner, this technique allows for causal identification of treatment effects. Unlike standard regression models, nearest neighbor matching weights observations to make the control group more similar to treated prisoners than would otherwise be the case (Angrist & Krueger, 1999). The key identifying assumption of these models is that both treated and matched untreated prisoners would be expected to have the same recidivism outcomes in the absence of treatment. Matching is thus justified when the set of observable characteristics is rich enough to capture the underlying differences between groups. Fortunately, Iowa's administrative data is incredibly detailed and allows for prisoners to be matched on many potentially relevant

[5]All estimation is done in Stata using the ado file developed by Leuven et al. (2015).

characteristics. Matching is also only appropriate where general equilibrium effects are not important. That is, if treatment could reasonably be expected to influence the untreated group as well as the treated group, matching would be inappropriate. This seems unlikely in this setting.

The matching itself is done using three distinct sets of observable characteristics. In the first case, prisoners are matched only on LSI-R score. To better match the treatment and control group prisoners, in subsequent specifications prisoners are matched on LSI-R score as well as the universe of variables described earlier.

Importantly, all estimates from this estimation strategy will yield average treatment effects. This implies that programming may make certain individuals less likely to recidivate even if there is not a significant overall effect. Unobservable prisoner characteristics, such as degree of program need and motivation, may be both important predictors of success and sufficiently rare among those experiencing programming that they fail to show up in estimates of aggregate effects, particularly if other program participants become more likely to recidivate.

Because each program category has a different number of eligible, active, and successful participants, the number of useable observations changes dramatically across regressions. Specifically, Table 2 details the number of treatment and control group observations available. For each program category, the total number of prisoners eligible for the indicated program is given in the first column. Columns 2 and 3 indicate the number of prisoners in the treatment and control groups for specifications that estimate the impact of program attendance on recidivism. Similarly, Columns 4 and 5 describe the number of observations available for specifications that consider the impact of successful program completion. Unfortunately, in three cases, the number of observations in the control group is so low that reliable estimates using nearest neighbor matching model are not possible. Specifically, the impact of participating in reentry treatment or successfully completing a program in either the moving on or sex offender treatment categories cannot be estimated. Moreover, any program that has double digit observations in either the treatment or control groups will necessarily have large standard errors reflecting highly variable point estimates. These programs include participation in moving on and sex offender treatment, and the successful completion of anger management, domestic abuse treatment, family treatment, mental health treatment, MIFVPP, reentry treatment, and victim treatment.

4 Findings

The primary results are presented in Table 3. In Table 3, each cell is the result of a unique regression similar to the model presented in Equation 1. Each row indicates the program considered in that specification. Columns 1-3 present results comparing the recidivism outcomes of prisoners that actively participated in the indicated program to those that were eligible but did not participate due to factors beyond their control. Columns 4-6 present results comparing the recidivism outcomes of prisoners that successfully completed the program to those that participated but were not able to complete it. For both program participation and completion, results are presented based on three distinct matching models. In Columns 1 and 4, prisoners are matched only on LSI-R score. As described above, LSI-R score is a measure created by the Iowa Department of Corrections that estimates how likely a prisoner is to recidivate within one year of release. In Columns 2 and 5, LSI-R score is included as well as a number of other potentially important characteristics including gender, number of dependents, whether the prisoner had recidivated in the past, total number of crimes committed, number of violent crimes committed, race dummies, primary facility security level, privilege level, the number of moves the prisoner experienced, year of release, and crime type dummies. Both linear and quadratic trends in age, average number of misconducts per day, average number of visits per day, number of days incarcerated, and number of days on probation are also included. Columns 3 and 6 are identical to Columns 2 and 5 except that all continuous variables are measured using decile bins instead of linear and quadratic terms.

Across all models, there are few cases where programming can be seen to significantly reduce recidivism. No program, for either participation or success, consistently yields negative and significant coefficients across specifications. In fact, among the 87 estimated coefficients, only three yield significant negative coefficients. Moreover, the standard errors in Table 3 have not been adjusted to account for multiple hypothesis testing despite the fact that there are 87 distinct hypotheses in this table alone. To account for this, the standard errors on each specification need to be inflated (Shaffer, 1995). After properly inflating standard errors to account for this issue using a simple sequential Bonferroni procedure, only job training is found to significantly reduce recidivism at the 10% significance level and even that is only significant in one of the six specifications it appears in (Benjamini & Hochberg, 1995). The only program that yields consistently significant estimates across all three matching strategies is participation in employment services. The results suggest that participants in this program are 10-14% more likely to recidivate than non-participants. Interestingly, even after adjusting the standard errors to account for multiple hypothesis testing, two of the three specifications for employment services participation remain significant at the 10% level.

Table 4 is identical to Table 3 but limits recidivism to only new crimes. As with total recidivism, the results show no consistent, significant negative effects of program participation or success. There is again some evidence that participation in employment services increases a prisoner's probability of recidivating but after correcting the standard errors to account for multiple hypothesis testing only the estimates in Column 1 remain significant at the 10% level. Overall, the results are sensitive to the variables used to match treated and control observations suggesting that large causal effects from any type of program are unlikely.

In interpreting these results, it should be noted that any bias not removed through sample selection and matching likely pushes the estimates towards a negative relationship between program completion and recidivism. Suppose, for example, that people who successfully complete programs are more focused and disciplined on average. This may allow these people to complete programs more quickly and would also be an asset in avoiding recidivism upon release. To the extent that this trait is unobservable and not controlled for within a matching strategy, this would cause the results to incorrectly suggest that program completion caused reductions in recidivism.

One plausible explanation for the lack of significant results is that recidivism rates in Iowa are sufficiently low that further gains are difficult or impossible to pick up. Recall that the new crime recidivism rate in Iowa is only 20% implying that many of the prisoners in the sample would not be expected to recidivate regardless of program participation. This concern is directly related to a lack of observations as small gains will be more difficult to pick up among fewer observations. To test this hypothesis, the next section examines only those prisoners deemed most likely to recidivate based on their LSI-R scores.

4.1 Robustness - Prisoner's Most Likely to Recidivate

In this section, I restrict the analysis to prisoners in the three highest risk categories according to LSI-R score.[6] This increases the average overall recidivism rate to 33% and the new crime recidivism rate to 21%. Table 5 indicates the number of observations available for each program. Unfortunately, with the sample restricted to the highest risk offenders, certain programs see significant drops in observations and estimation of the effect of these programs is not possible. Specifically, the reentry treatment and sex offender treatment program categories are too rare to be estimated for either participation or success. Furthermore, the impact of successfully completing anger management, domestic abuse treatment, and moving on cannot be estimated.

Results are presented in Table 6. This table is organized identically to Table 3 but restricts the sample to prisoners most likely to recidivate. As in the previous tables, there is no evidence that suggests any program significantly reduces recidivism. Instead, employment services programming is again found to increase a prisoner's probability of recidivating. The

[6]The sample can also be restricted to LSI-R categories 4, and 5. Results presented in this section are consistent when category 3 is excluded.

most significant difference among these results relative to the results for all prisoners is the strikingly large and statistically significant coefficient on mental health treatment which suggests that successful completers of that program are 45% more likely to recidivate than prisoners who participate in the program but do not successfully complete it. As in the earlier tables, results are presented without adjusting for multiple hypothesis testing. After this adjustment, only the coefficients on employment services, in Columns 1 and 2 and on Job Training in Column 1 remain significant.

The results among new crime recidivism are presented in Table 7. Looking exclusively at new crime recidivism makes the results slightly more optimistic, with successful completion of life skills programming weakly significant but suggesting a 34% decrease in recidivism and mental health treatment no longer significantly positive. Overall however, this Table further confirms a general lack of significant effects of programming on recidivism.

Another way to focus the analysis on those prisoners potentially most likely to benefit from programming is to limit the sample to the prisoners who had previously recidivated. Consistent with the prior literature, this group recidivates more often than those who have not previously recidivated. 54% of the individuals in the sample who had previously recidivated recidivate again during the sample window with 36% of this group committing new crimes. To explore this possibility, the analysis above is replicated after restricting the sample to prisoners that had previously recidivated.[7] The findings are broadly consistent with earlier results. Most programs do not have any significant effect on recidivism among prior recidivists and where significant effects appear, the sign of the estimates suggest some programs may actually be increasing recidivism.[8] The one exception is participation in job training which yields significant negative coefficients in two of the three specifications estimated for both new crime and total recidivism. On the other hand, once adjustments are

[7]Tables available upon request.

[8]Participation in either employment services programming or MIVFPP is found to increase both technical and new crime recidivism in two of the three specifications considered. Participation in a domestic violence program increases new crime recidivism in two of the three specifications considered.

made for multiple hypothesis testing, even these results become insignificant.

5 Discussion and Limitations

The lack of significant effects are most likely due to a combination of factors. First, many programs are simply not effective at reducing recidivism. This is in part because not all programs are designed with the explicit goal of recidivism reduction. For example, substance abuse care programs are typically designed to aid prisoners as they transition from drug and alcohol dependencies outside of prison to hopefully cleaner living while incarcerated. While this care has the potential to reduce recidivism after release a reduction in drug related misconducts during incarceration should be considered a successful outcome of this program. Second, program implementation is often inconsistent even within the relatively narrow program categories considered. It is possible that within each program category, certain specific courses are working quite well and are effectively reducing recidivism. In the aggregate however, these positive effects are washed out by a multitude of programs not working as intended. Finally, it may be the case that significant gains from these programs are occurring, but the available sample size is too small to pick up significant effects. The evidence for this possibility is mixed. Among programs with at least one thousand observations in the control group (the control group is consistently smaller than the treatment group), I find significance only on positive coefficients for substance abuse care, substance abuse treatment, and cognitive treatment. Successfully completing education, a category that also have more than 1000 control observations, yields no significant results and positive coefficients in two of the three specifications. On the other hand, it is entirely possible that certain programs are both rare and effective at reducing recidivism. For example, in the primary results, successful completion of the substance abuse treatment program has only 148 control observations but the point estimate suggests an 11% reduction in recidivism in the preferred specification.

Where there are significant negative effects, significance often comes only when matching is based only on LSI-R scores. This implies that these results are driven by relatively poor matching of treatment and control prisoners rather than a real effect of programming. This is an important consideration as matching only on LSI-R scores is most similar to earlier research in this area. To the extent that improved matching limits our ability to find significant recidivism reductions, this result suggests that earlier papers with more optimistic conclusions may suffer from selection bias.

In this light, one key benefit of the empirical strategy is that any potentially confounding factors must be differentially applicable to prisoners that either participated in or successfully completed a given type of program. For example, many papers have shown that the lack of employment opportunities available to former prisoners is a significant factor in recidivism. However, for employment opportunities to influence the results, it must be the case that program participants and program completers are systematically more likely to have difficulty finding employment than individuals that were eligible for programming but did not participate. To the extent that all former prisoners face similarly high barriers to securing employment, these barriers will have no impact on the estimates.

That programming is consistently found to be ineffective on average implies that, as currently implemented in Iowa, none of the programs considered in this analysis are a cost effective method of reducing recidivism. On the other hand, the only outcome considered here is recidivism. As such, there may be a variety of benefits accruing from in-prison programming not estimated in this analysis. For example, a number of studies have found that behavioral treatment programs significantly reduce misconduct during incarceration (French & Gendreau, 2006; Steiner & Wooldredge, 2008). As such, prison programs may represent an important tool that aids in managing inmates and offers value by improving the safety of both inmates and correctional officers even in the absence of recidivism reductions (Chamberlain, 2012). Much more research is needed before a clear policy recommendation about the future of in-prison programming can be made. This research does not imply that individual programs need to be removed, but instead contributes to the larger literature on the total value of prison programming. More research is needed to confirm the findings presented here in other states with different methods of program implementation and higher recidivism rates. Similarly, we do not yet have a full understanding of the benefits that programming may provide outside of recidivism. For example, it is possible that participants in employment training find better jobs more quickly after release even if this improvement does not lead to reduced recidivism overall.

6 Conclusion

A large body of literature has considered the impact of a variety of prison programs on recidivism. A key empirical challenge in this sort of analysis is the potential for unobservable differences between program participants and non-participants to obscure the causal influence of programming. To minimize this potential, a unique identification strategy that matches program participants to prisoners that were eligible for the program but did not participate due to factors beyond their control is employed. Limiting the control group in this way significantly reduces the probability that participating prisoners have different unobservable characteristics than non-participants such as discipline and motivation.

After considering 16 unique program categories, there is no evidence that any prison program significantly reduces recidivism rates among either participants or successful completers. This result holds for both total and new crime recidivism as well as among those prisoners deemed to carry the highest risk of recidivating. Three potential explanations for this finding deserve discussion. First, the programs studied here may simply be ineffective at reducing recidivism. Second, conversations with the IDOC suggested that program implementation is widely varied across facilities and across time. It is therefore possible, or even likely, that inconsistent program implementation has mitigated the overall impact of the programs themselves. Finally, despite an innovative empirical design, it is possible that the unobservable characteristics of program participants and completers are still meaningfully different from non-participants. If non-participants were less likely to recidivate than program participants in the absence of treatment and the actual effect of treatment was to reduce recidivism, the results would be biased towards finding nothing. It is more likely, however, that program non-participants were more likely to recidivate than participants in the absence of treatment. This would bias the results towards finding a recidivism reduction effect even if programming did nothing. The lack of significant effects suggest that the methodology employed here has successfully mitigated this potential bias and indicate that earlier studies finding substantial program benefits may suffer from selection bias.

This paper adds to a long literature assessing the impact of prison programming. It is, however, among the first to offer plausibly causal estimates for such a wide variety of programs. A significant policy implication from this research is that program type and focus are likely less important than program quality. In short, the answer to the question of what works in prison programming is less an issue of which programs are offered and much more an issue of how a program is implemented. Future research should carefully consider and compare across similar programs implemented differently across facilities to determine what strategies are most effective at achieving tangible results.

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7 Tables

Table 1: Summary Statistics

	Mean	Standard Deviation
Recidivism Rate	0.306	0.461
Recidivism (New Crimes)	0.195	0.396
Recidivism (Technical)	0.111	0.314
Male	0.875	0.330
Dependents	0.543	0.498
LSI-R Score	31.35	7.78
Prior Recidivist	0.524	0.499
Total Crimes	3.214	1.877
Violent Crimes	0.636	1.142
White	0.677	0.468
Black	0.239	0.426
Hispanic	0.060	0.238
Other Race	0.026	0.158
Minimum Security	0.102	0.251
Medium Security	0.719	0.365
Maximum Security	0.013	0.084
Cell Moves	0.675	0.736
Age at Release	35.80	10.64
Misconducts per Day	0.005	0.012
Visits per Day	0.044	0.089
Days Incarcerated	556.16	711.68
Days Probation	34.27	77.72
Drug Crime	0.321	0.467
Property Crime	0.296	0.456
Violent Crime	0.214	0.410
Public Order Crime	0.153	0.360
Other Crime	0.016	0.124
N	10,583	

Recidivism Rate includes both new crime recidivism and parole violations severe enough to cause the individual to return to prison (technical). LSI-R score estimates the probability a prisoner will recidivate within one year of release based on observable characteristics. Facility security level is based on the facility that the prisoner spent the most time in during their incarceration. Cell moves indicates the number of times a prisoner changed cells within the same facility during their incarceration. Crime Types are coded as one if the prisoner's most severe conviction was for a crime of the indicated type and zero otherwise.

Table 2: Observations in Each Regression

		Active		**Success**	
	Eligible	Participated	Control	Success	Control
Anger Management	850	576	274	553	23
Cognitive Treatment	2,974	2,090	884	1,954	136
Domestic Abuse Treatment	1,042	705	337	684	21
Education	3,805	3,231	574	2,072	1,159
Employment Services	1,383	976	407	701	275
Family Treatment	618	475	143	441	34
Job Training	1,182	896	286	769	127
Life Skills	5,585	5,140	445	4,983	157
Mental Health Treatment	791	493	298	247	51
MIFVPP	1,024	694	330	669	25
Moving On	213	139	74	119	20
Reentry Treatment	500	495	5	465	30
Sex Offender Treatment	520	474	46	454	20
Substance Abuse Care	4,911	3,733	1,178	3,226	507
Substance Abuse Treatment	3,634	2,386	1,248	2,238	148
Victim Treatment	1,500	1,025	475	966	59

Each cell indicates the number of observations available to examine the impact of the indicated program on recidivism. Prisoners are counted as eligible if they were designated as eligible for the indicated program and did not avoid participation in or fail a program because of factors within their control.

Table 3: Propensity Score Matching - All Recidivism

	Active			**Success**		
	LSI-R Only	Quadratic Trends	Decile Bins	LSI-R Only	Quadratic Trends	Decile Bins
Anger Management	-0.0101	0.0069	-0.0313	0.1212	0.2143	0.2249
	(0.0391)	(0.0564)	(0.0631)	(0.0934)	(0.2556)	(0.2636)
Cognitive Treatment	0.0459**	0.0133	0.0421	-0.0191	0.0308	0.1070
	(0.0188)	(0.0283)	(0.0291)	(0.0468)	(0.0948)	(0.1348)
Domestic Abuse Treatment	0.0546*	0.0879*	0.0426	-0.0205	0.1799	0.2922
	(0.0328)	(0.0481)	(0.0614)	(0.1445)	(0.3762)	(0.3601)
Education	-0.0076	0.0003	0.0006	0.0249	0.0019	0.0005
	(0.0219)	(0.0322)	(0.0355)	(0.0179)	(0.02774)	(0.0304)
Employment Services	0.1012***	0.1434***	0.1385***	-0.0299	-0.0228	-0.0014
	(0.0263)	(0.0443)	(0.0505)	(0.0370)	(0.0638)	(0.0649)
Family Treatment	0.0474	0.0756	0.1057	0.0472	-0.3303	0.2486
	(0.0496)	(0.1004)	(0.1051)	(0.0873)	(0.2471)	(0.2719)
Job Training	-0.1678***	-0.0022	-0.1453	0.0972	0.1523*	0.1185
	(0.0432)	(0.1125)	(0.1198)	(0.0478)	(0.0867)	(0.1057)
Life Skills	0.0152	0.0181	-0.0255	-0.0752	0.1112	0.0871
	(0.0253)	(0.0592)	(0.0588)	(0.0467)	(0.1138)	(0.1856)
Mental Health Treatment	-0.0960***	0.0604	0.0302	0.2363***	0.3333	0.2941
	(0.0366)	(0.0708)	(0.0727)	(0.0790)	(0.1725)	(0.1797)
MIFVPP	0.0549	0.0476	0.0562	-0.0336	-0.3605	0.2411
	(0.0331)	(0.0482)	(0.0615)	(0.1420)	(0.2838)	(0.3967)
Moving On	0.1129*	0.1045	0.1172			
	(0.0626)	(0.1303)	(0.1292)			
Reentry Treatment				0.0756	0.1209	-0.3480
				(0.1173)	(0.1977)	(0.2850)
Sex Offender Treatment	0.0207	0.1674	0.1721			
	(0.0898)	(0.2730)	(0.2961)			
Substance Abuse Care	-0.0122	0.0707*	0.0440	-0.0366	-0.1452	0.0501
	(0.0237)	(0.0417)	(0.0470)	(0.0545)	(0.0905)	(0.1046)
Substance Abuse Treatment	0.0344**	0.0122	-0.0067	0.02516	-0.08217	-0.10633
	(0.0173)	(0.0235)	(0.0249)	(0.03769)	(0.07057)	(0.08093)
Victim Treatment	0.0233	0.0439	0.0586	-0.2779***	0.1305	0.2015
	(0.0287)	(0.0424)	(0.0416)	(0.0921)	(0.1958)	(0.2890)

Each cell represents a unique specification with recidivism as the dependent variable and either participation in (Columns 1-3) or completion of (Columns (4-6) the indicated program as the key independent variable using a nearest neighbor matching model as presented in Equation 1. Columns 1 and 4 match prisoners based only on LSI-R score. Columns 2 and 5 also match prisoners many other characteristics as described in the text. Columns 3 and 6 match prisoners on the same characteristics as Columns 2 and 5 use decile bins rather than linear and quadratic terms for continuous variables. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors in parentheses.

Table 4: Propensity Score Matching - New Crimes

	Active			**Success**		
	LSI-R Only	Quadratic Trends	Decile Bins	LSI-R Only	Quadratic Trends	Decile Bins
Anger Management	-0.0132	0.0087	-0.0017	0.0127	0.1109	0.1138
	(0.0343)	(0.0475)	(0.0562)	(0.0928)	(0.2554)	(0.2632)
Cognitive Treatment	0.0314**	0.0335	0.0574**	-0.0065	-0.0056	0.0664
	(0.0159)	(0.0238)	(0.0245)	(0.0404)	(0.0823)	(0.1115)
Domestic Abuse Treatment	0.0572**	0.0894**	0.0525	0.0380	0.1306	0.2143
	(0.0290)	(0.0423)	(0.0529)	(0.1343)	(0.3569)	(0.2757)
Education	-0.0087	0.0241	0.0375	0.0006	-0.0010	0.0043
	(0.0186)	(0.0274)	(0.0296)	(0.0151)	(0.0237)	(0.0257)
Employment Services	0.0829***	0.0963***	0.0944**	-0.0215	-0.0328	-0.0200
	(0.0207)	(0.0350)	(0.0373)	(0.0317)	(0.0559)	(0.0546)
Family Treatment	0.0442	0.1015	0.1189	0.0382	0.1239	0.1730
	(0.0400)	(0.0764)	(0.0730)	(0.0644)	(0.1687)	(0.1470)
Job Training	-0.1350***	0.0313	-0.1892*	0.0146	0.0755	0.0690
	(0.0395)	(0.1017)	(0.1110)	(0.0415)	(0.0757)	(0.0953)
Life Skills	-0.0004	0.0245	0.0403	-0.0006	0.0450	0.0132
	(0.0223)	(0.0511)	(0.0508)	(0.0400)	(0.0971)	(0.01565)
Mental Health Treatment	-0.1002***	0.0000	-0.0705	0.0385	0.0784	0.1176
	(0.0323)	(0.0649)	(0.0694)	(0.0677)	(0.0159)	(0.1472)
MIFVPP	0.0572	0.0605	0.0605	-0.0486	-0.4295	0.1584
	(0.0294)	(0.0422)	(0.0544)	(0.1351)	(0.2703)	(0.3782)
Moving On	0.0869**	0.1045***	0.1016			
	(0.0401)	(0.0265)	(0.0654)			
Reentry Treatment				0.0756	0.0176	-0.4559*
				(0.1021)	(0.1511)	(0.2553)
Sex Offender Treatment	0.0243	0.0343	0.0558			
	(0.0590)	(0.2061)	(0.2177)			
Substance Abuse Care	-0.0031	-0.0035	-0.0238	0.0069	0.0480	0.0447
	(0.0146)	(0.0240)	(0.0245)	(0.0198)	(0.0349)	(0.0396)
Substance Abuse Treatment	-0.0088	-0.0034	-0.0382*	-0.0227	0.0045	0.0313
	(0.0151)	(0.0204)	(0.0215)	(0.0480)	(0.0790)	(0.0901)
Victim Treatment	0.0115	0.0293	0.0459	-0.2295***	0.1013	0.1118
	(0.0244)	(0.0349)	(0.0344)	(0.0827)	(0.1708)	(0.2466)

Each cell represents a unique specification with new crime recidivism as the dependent variable and either participation in (Columns 1-3) or completion of (Columns (4-6) the indicated program as the key independent variable using a nearest neighbor matching model as presented in Equation 1. Columns 1 and 4 match prisoners based only on LSI-R score. Columns 2 and 5 also match prisoners many other characteristics as described in the text. Columns 3 and 6 match prisoners on the same characteristics as Columns 2 and 5 use decile bins rather than linear and quadratic terms for continuous variables. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors in parentheses.

Table 5: Observations in Each Regression - LSIR Categories 3, 4, and 5

		Active		**Success**	
	Eligible	Participated	Control	Success	Control
Anger Management	681	445	236	430	15
Cognitive Treatment	2,411	1,681	731	1,566	114
Domestic Abuse Treatment	904	603	301	583	20
Education	3,178	2,692	486	1,680	1,012
Employment Services	1,102	767	231	536	231
Family Treatment	479	359	120	334	25
Job Training	886	645	241	549	96
Life Skills	4,452	4,056	396	3,933	123
Mental Health Treatment	705	264	441	45	219
MIFVPP	893	597	296	574	23
Moving On	176	111	65	91	20
Reentry Treatment	386	384	2	358	26
Sex Offender Treatment	319	285	34	268	17
Substance Abuse Care	4,128	3,092	1,036	2,675	417
Substance Abuse Treatment	2,923	1,846	1,077	1,719	127
Victim Treatment	1,145	738	407	687	51

Each cell indicates the number of observations available to examine the impact of the indicated program on recidivism. Prisoners are counted as eligible if they were designated as eligible for the indicated program and did not avoid participation in or fail a program because of factors within their control. Prisoners in LSI-R categories 1 and 2 are not included in these values. LSI-R score estimates the probability a prisoner will recidivate within one year of release based on observable characteristics. LSI-R scores are grouped into 5 categories with higher values indicating higher recidivism risk.

Table 6: Propensity Score Matching - All Recidivism - LSIR Categories 3, 4, and 5

	Active			Success		
	LSI-R Only	Quadratic Trends	Decile Bins	LSI-R Only	Quadratic Trends	Decile Bins
Anger Management	-0.0177	-0.0449	-0.0517			
	(0.0411)	(0.0591)	(0.0648)			
Cognitive Treatment	0.0427**	-0.0280	-0.0220	0.0088	-0.0485	0.0633
	(0.0210)	(0.0356)	(0.0358)	(0.0512)	(0.1145)	(0.1490)
Domestic Abuse Treatment	0.0497	0.0133	0.0349			
	(0.0346)	(0.0491)	(0.0590)			
Education	-0.0021	0.0501	0.0212	0.0206	0.0494	0.0518
	(0.0237)	(0.0341)	(0.0397)	(0.0193)	(0.0300)	(0.0328)
Employment Services	0.1115***	0.1773***	0.1632***	-0.0710*	-0.0056	0.0355
	(0.0294)	(0.0455)	(0.0588)	(0.0402)	(0.0717)	(0.0739)
Family Treatment	0.0683	-0.0940	0.1516	0.0958	0.2050	0.3161
	(0.0548)	(0.1305)	(0.1684)	(0.0981)	(0.2974)	(0.3465)
Job Training	-0.1587***	-0.2186	0.0501	0.0590	0.1642	0.1698
	(0.0393)	(0.1416)	(0.1308)	(0.0563)	(0.1070)	(0.1345)
Life Skills	0.0223	-0.0402	-0.0096	-0.0848*	0.1721	-0.2288
	(0.0256)	(0.0707)	(0.0621)	(0.0516)	(0.1602)	(0.2213)
Mental Health Treatment	-0.0998***	0.0492	-0.0303	0.2141***	0.2889	0.4545**
	(0.0379)	(0.0803)	(0.0809)	(0.0835)	(0.2256)	(0.1821)
MIFVPP	0.0491	0.0706	0.0790	0.0549	0.1843	0.2482
	(0.0350)	(0.0519)	(0.0628)	(0.1496)	(0.3343)	(0.3962)
Moving On	0.1144	-0.1698	0.1373			
	(0.0705)	(0.1429)	(0.1405)			
Substance Abuse Care	0.0442**	0.0226	0.0385	-0.00485	0.0710	-0.0718
	(0.0175)	(0.0280)	(0.0294)	(0.0263)	(0.0504)	(0.0701)
Substance Abuse Treatment	0.0451**	0.0103	-0.0033	-0.0757	-0.1425	0.0000
	(0.0188)	(0.0278)	(0.0283)	(0.0596)	(0.1054)	(0.1244)
Victim Treatment	0.0328	0.0515	0.0027	-0.3369***	0.1857	0.2188
	(0.0301)	(0.0552)	(0.0537)	(0.1060)	(0.2037)	(0.2871)

Each cell represents a unique specification with recidivism as the dependent variable and either participation in (Columns 1-3) or completion of (Columns (4-6) the indicated program as the key independent variable using a nearest neighbor matching model as presented in Equation 1. Columns 1 and 4 match prisoners based only on LSI-R score. Columns 2 and 5 also match prisoners many other characteristics as described in the text. Columns 3 and 6 match prisoners on the same characteristics as Columns 2 and 5 use decile bins rather than linear and quadratic terms for continuous variables. Prisoners in LSI-R categories 1 and 2 are not included in these results. LSI-R score estimates the probability a prisoner will recidivate within one year of release based on observable characteristics. LSI-R scores are grouped into 5 categories with higher values indicating higher recidivism risk. * p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01. Standard errors in parentheses.

Table 7: Propensity Score Matching - New Crimes - LSIR Categories 3, 4, and 5

	Active			**Success**		
	LSI-R Only	Quadratic Trends	Decile Bins	LSI-R Only	Quadratic Trends	Decile Bins
Anger Management	-0.0258	-0.0652	-0.0584			
	(0.0365)	(0.0534)	(0.0558)			
Cognitive Treatment	0.0125	0.0024	0.0238	0.0247	-0.0817	0.0478
	(0.0180)	(0.0300)	(0.0301)	(0.436)	(0.0963)	(0.1263)
Domestic Abuse Treatment	0.0474	0.0433	0.0067			
	(0.0312)	(0.0436)	(0.0538)			
Education	-0.0057	0.0579	0.0201	0.0031	0.0381	0.0322
	(0.0203)	(0.0284)	(0.0334)	(0.0164)	(0.0253)	(0.0269)
Employment Services	0.0811***	0.0939***	0.0783	-0.0491	0.0093	0.0355
	(0.0230)	(0.0367)	(0.0472)	(0.0346)	(0.0612)	(0.0613)
Family Treatment	0.0465	0.0940	0.1166	0.0988*	0.1398	0.2241
	(0.0445)	(0.0991)	(0.1284)	(0.0639)	(0.1508)	(0.2014)
Job Training	-0.1070***	-0.2233*	0.0250	-0.0287	0.0784	0.0900
	(0.0361)	(0.1303)	(0.1220)	(0.0506)	(0.0936)	(0.1216)
Life Skills	0.0006	-0.0409	0.0673	-0.0227	0.0577	-0.3407*
	(0.0228)	(0.0613)	(0.0541)	(0.0459)	(0.1449)	(0.2107)
Mental Health Treatment	-0.1006***	-0.0227	-0.1023	0.0066	0.1778	0.1591
	(0.0336)	(0.0723)	(0.0763)	(0.0704)	(0.1455)	(0.1765)
MIFVPP	0.0476	0.0538	0.0319	-0.0200	0.0931	0.1763
	(0.0316)	(0.0468)	(0.0569)	(0.1444)	(0.3221)	(0.3793)
Moving On	0.0908**	0.0849	0.1078***			
	(0.0455)	(0.0852)	(0.0309)			
Substance Abuse Care	-0.0053	-0.0307	-0.0307	0.0053	0.0572	-0.0643
	(0.0157)	(0.0252)	(0.0269)	(0.0222)	(0.0422)	(0.0590)
Substance Abuse Treatment	-0.0017	0.0054	-0.0304	-0.0438	-0.0902	0.0687
	(0.0165)	(0.0239)	(0.0245)	(0.0533)	(0.0945)	(0.1090)
Victim Treatment	0.0060	0.0068	-0.0231	-0.2455***	0.1374	0.1310
	(0.0258)	(0.0475)	(0.0454)	(0.0965)	(0.1784)	(0.2665)

Each cell represents a unique specification with new crime recidivism as the dependent variable and either participation in (Columns 1-3) or completion of (Columns (4-6) the indicated program as the key independent variable using a nearest neighbor matching model as presented in Equation 1. Columns 1 and 4 match prisoners based only on LSI-R score. Columns 2 and 5 also match prisoners many other characteristics as described in the text. Columns 3 and 6 match prisoners on the same characteristics as Columns 2 and 5 use decile bins rather than linear and quadratic terms for continuous variables. Prisoners in LSI-R categories 1 and 2 are not included in these results. LSI-R score estimates the probability a prisoner will recidivate within one year of release based on observable characteristics. LSI-R scores are grouped into 5 categories with higher values indicating higher recidivism risk. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors in parentheses.

8 Appendix

Table A1: Categorization of Program Non-Participation and Failure

Non-Participation		Failure	
Outside of Prisoner Control	Within Prisoner Control	Outside of Prisoner Control	Within Prisoner Control
Case Manager Discretion	Non-Compliant/Behavioral	Case Manager Discretion	Absconded/Escaped
Court Discretion	Refused Treatment	Court Discretion	Non-Compliant/Behavioral
Inappropriate Referral	Revoked	Inappropriate Referral	Refused Treatment
Ineligible to Attend	Violator Program Placement	Ineligible to Attend	Revoked
Not Admitted		Program Elimination	Violator Program Placement
Program Elimination		Referred to Alt. Intervention	
Referred to Alt. Intervention		Released on Bond	
Released on Bond		Residential Placement	
Residential Placement		Sentence Terminated	
Sentence Terminated		Transferred	
Transferred			

Table A2: Recidivism Probability by LSIR Risk Category

	All Recidivism	New Crime	Observations
1-Low	0.04	0.02	138
2-Med/Low	0.22	0.13	1,625
3-Medium	0.30	0.18	4,408
4-Med/High	0.34	0.22	3,119
5-High	0.40	0.29	1,293