The effect of prison-based college education programs on recidivism: Propensity Score Matching approach

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A R T I C L E   I N F O

Purpose: Most prior research reports that prison-based college education reduces recidivism, but fails to address the potential problem of self-selection bias. The primary purpose of this study is to examine the true treatment effect of prison-based college education on recidivism.

Methods: Using data acquired from New York State, we use the Propensity Score Matching (PSM) method to control for self-selection bias. The recidivism rate is compared between the treatment and matched comparison group. Also, fixed-effects logistic regression and Cox regression models are utilized to measure the effect of prison-based college programs on recidivism.

Results: We find that the recidivism rates within three years after release for college program completers and a PSM derived comparison group were 9.4% and 17.1% respectively. However, the recidivism rate for a comparison group not derived by the PSM method was more than double the rate of the PSM derived comparison group. Fixed-effects logistic regression and Cox regression models also confirm that prison-based college programs have a positive effect on reducing recidivism.

Conclusions: The results of this study suggest that inflated estimates of the treatment effect may result when research does not take self-selection bias into account and apply appropriate methods to compensate for that bias.

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Introduction

While it can be an oversimplification of a complex process, there has been a historical tendency to emphasize different types of prison-based education depending upon the dominant correctional goal of a given time period. The development of nineteenth century American prisons as places to punish convicted criminals illustrates how different educational aims were manifested in a prison setting. For example, those who saw the goal of punishment as transformative tended to focus on the moral instruction of offenders to teach them how to live non-criminal lives (see Goldsmith, 1997). Initially, the Quakers, a private sector religious group that was influential in the development of the Pennsylvania Prison Model, sought to create an environment that would foster self-reflection in those who were imprisoned by providing offenders with Bibles to facilitate their “moral” education (Pollock, 1997). The moralistic approach was later combined with the provision of the academic education provided in the mid-1800’s with the development of tax-payer financed public schools that was in part designed to “Americanize” newly arriving immigrants. In contrast, the State of New York took a different track, developing an alternative model, known as the Auburn Model. This model was essentially designed to take advantage of a large and free source of labor (Hawkins & Alpert, 1989). It was not a great leap from there for proponents of education as a transformative experience to focus on occupational training that would provide offenders with practical job skills upon release.

So, historically, prison-based education has been the product of both the private and public spheres. More recently, there continue to be private sector advocates of higher education in prisons who justify the provision of such programs on humanitarian grounds (Hower, 2012). In the public sector, higher academic education became available to prisoners as the Federal Government established the Pell Grants Program in the early 1970’s. Pell Grants were established to provide low income individuals with the opportunity to enroll in college programs. Unlike the college loans provided to low and middle income individuals under the Higher Education Act of 1965, Pell Grants did not have to be repaid. Pell money is awarded to students through participating institutions as a component of the institution’s financial aid assessment of individual students. The existence of these grants paid directly to colleges is what made it possible for the colleges receiving Pell money to provide postsecondary higher education to criminal offenders serving time in state prisons (see Cervantes et al., 2005).

While college programs are provided in many states in the hope of rehabilitating ex-offenders, there is not a large body of research...
examining the impact of prison-based college education on recidivism. The existing literature generally reports a positive relationship in which prison-based college programs are correlated with a reduction in recidivism for program participants (see Clark, 1991; Esperian, 2010; Lichtenberger & Onyewu, 2005; Torre, 2001). However, a review of this literature indicates that the methodologies used to generate and analyze the data ignore the likelihood of self-selection bias (Brazzell, Crayton, Mukamal, Solomon, & Lindahl, 2009; Lewis, 2006). This can be a potentially major threat to internal validity that may inflate the estimates of the outcome measure (generally recidivism) thereby overstating the treatment effect.

While randomized controlled trials make the most valid assessment of the treatment effect, it would be very difficult to implement the randomized experimental design for individuals who are incarcerated because of human subjects concerns as well as the supremacy of security procedures that must be employed in prison settings. However, there are currently more sophisticated quasi-experimental methods available to researchers that make it possible to minimize the self-selection threat to internal validity (see Morgan & Winship, 2007). The Propensity Score Matching (PSM) method is a case in point. The basic goal of PSM is to identify observationally similar individuals who are not in the treatment group. These observationally similar individuals become a counterfactual for the treatment group that makes it possible to determine what would have happened to the treatment group in the absence of the treatment. Identifying individuals sharing similar attributes to the treatment group requires a consideration of the complete range of covariates upon which treatment and non-treatment individuals may differ. PSM is a sophisticated and innovative method that considers the complete range of covariates (Heinrich, Maffoli, & Vásquez, 2010).

In this paper, we have set out to address the question of whether self-selection is an actual threat to internal validity and if so, what the true effect might be. Toward this end we examine the effect of prison-based college education on recidivism using New York State data with two objectives in mind. First, we employ the PSM method to generate a matched comparison group for our analysis that is designed to eliminate the effects of self-selection bias. We then compare the levels of our recidivism outcome measure for those who completed prison-based college programs and those who did not participate in the programs before and after the application of the PSM method. This enables us to determine whether research that does not control for self-selection bias produces inflated estimates of the treatment effect. Second, we investigate the effect of prison-based college education by using a fixed-effects logistic regression to measure the likelihood of re-arrest when a prisoner completes college education. Lastly, we take the length of time to re-arrest into consideration and employ a proportional hazards regression to compare hazard rates between those who completed prison-based college programs and their matched comparison group.

**Review of existing research**

Incarcerated individuals are less educated than the general population in a free society. Education can be a transformative experience providing those convicted of criminal behavior with a gateway into the law-abiding world (Gaes, 2008). Believing that education provides the means for people to live fulfilling and law-abiding lives, the criminal justice system provides various educational programs to offenders such as substance abuse programs, behavioral change programs, religious programs, educational or vocational programs, and so on. For example, the New York State Department of Corrections and Community Supervision requires inmates with no verified high school diploma or its equivalency to participate in educational classes until the diploma is obtained prior to release. The effect of various adult correctional programs are well reviewed in Aos, Miller, and Drake (2006a). They found that the basic adult education program reduces the recidivism rate by 5.1% and the vocational program reduces the rate by 12.6%. The study also reviewed the effect of other correctional programs including programs for drug, domestic violence, and sex offenders. While correctional institutions may provide a variety of programs, our study focuses on the effect of college programs in prison.

**Prison education generally**

Most studies of prison-based education programs examine the overall effect of correctional education programs and frequently do not distinguish between the effects of various types of programs such as vocational programs, high-school equivalent education or adult basic education, and postsecondary education. For example, Steurer, Smith, and Tracy (2001) studied the effect of correctional education programs in the states of Maryland, Minnesota, and Ohio. A total of 3,170 offenders were selected based on a quasi-experimental design, of which 43.3% were correctional education participants and 56.7% were non-participants. Recidivism was measured by re-arrest, re-conviction, and re-incarceration of offenders at any time within three years from release. The authors reported that correctional education participants had lower recidivism rates than non-participants. Similarly, Chappell (2004) found that postsecondary correctional education (PSCE) was correlated with lower rates of recidivism (re-arrest, re-conviction, and re-incarceration). In addition, Chappell indicated that recidivism rates were lower among the offenders who had completed the PSCE program than the offenders who had participated but did not complete the program.

Gerber and Fritsch (1995) meta-analyzed the findings of existing studies that evaluated the effect of adult academic and vocational correctional education programs. They concluded that there was a positive effect of the programs as evidenced by fewer disciplinary violations during incarceration, increases in employment opportunities upon release, and reductions in re-offending. Similarly, Wilson, Gallagher, and Mackenzie (2000) meta-analyzed the recidivism outcomes of 33 studies and found that participants in the educational, vocational, and correctional work programs were less likely to recidivate than non-participants after release. Postsecondary education programs showed the largest mean difference in recidivism between participants and non-participants. They also reported that educational programs appeared to be more effective at reducing recidivism than work-based programs.

**Prison-based college education**

While most studies have investigated the effect of general correctional treatment programs, only a few studies have focused on prison-based college programs. These studies seem to be in agreement that college programming in prison is correlated with a reduction in recidivism (Batiuk, Moke, & Rountree, 1997; Clark, 1991; Esperian, 2010; Fine et al., 2001; Lichtenberger & Onyewu, 2005; Winterfield, Coggeshall, Burke-Storer, Correa, & Tidd, 2009).

For example, Lichtenberger and Onyewu (2005) found that college program participants in Virginia correctional facilities had significantly lower recidivism rates than non-participants, with participants returning at a rate of 17.6%, while non-participants returned at a rate of 29.3%. Similarly, Fine and her colleagues (2001) studied the effect of college education on recidivism among female offenders at the Bedford Hills Correctional Facility in the State of New York. They found that non-participating female inmates returned to prison at almost four times the rate of female college participants (30% and 8% respectively). Batiuk, Moke, and Rountree (1997) also found that inmates obtaining an associates degree in a prison-based college education program at a medium security prison in Ohio had their odds of returning to prison within ten years reduced by 58% when compared to a randomly selected comparison group.
While existing research of the type reviewed above consistently show that prison-based college programs are effective in terms of reducing recidivism, it is possible that the program effects they report could be overestimated. For example, Fine and her colleagues (2001) made no attempt to develop a comparison group of non-participants that shared similar demographic and legal characteristics with the treatment group and compared the recidivism rate of program participants to the recidivism rate of the general female inmate population to demonstrate a treatment effect. Batikul, Moke, and Routtree (1997) also failed to produce an appropriate counterfactual by including high school dropouts in their control group who would not be eligible to take college courses.

As Lewis (2006) argues, studies that use very basic research designs do not consider the potential confounding effects of post-release factors or selection bias, and thus do not measure the actual treatment effect which may be why they all find ‘promising’ results. Selection bias, for example, may exist if those who participate in prison-based college programs are more motivated to make positive changes in their lives than those who do not participate in such programs and therefore, may be less likely to re-engage in criminal activity. Failure to control for selection bias is of course a threat to internal validity.

A more recent study by Winterfield et al. (2009) examined whether taking post-secondary coursework for which an inmate may receive college credits is related to lower recidivism rates. They collected administrative data from three states, in Indiana, Massachusetts, and New Mexico, however they reported that these data had limitations such as missing data, differing measures of recidivism, and differences between the treatment and control groups that made it difficult to develop an adequate counterfactual. They used a boosted regression method along with inverse probability weighting in an effort to deal with these problems.

In summary, while the literature consistently reports that correctional education in general, and prison-based college education in particular, decreases the likelihood of recidivism, a review of this literature reveals that it largely lacks any rigor in the research designs employed. Therefore, one of the purposes of this study is to determine whether the positive findings reported in the correctional education literature can be replicated with a more rigorous research design. Toward this end, we employ a Propensity Score Matching technique to create the environment that could attenuate possible selection problems and measure the actual effect of prison-based college programs.

**Current study**

As mentioned above, prior research examining the effectiveness of prison-based college programs suffered from both methodological and data problems. In fact, the most methodologically rigorous study within the literature reviewed was Winterfield et al. (2009) but its rigor was dictated by necessity in order to deal with shortcomings in the administrative data they were given to analyze. These researchers developed a comparison group based on demographic variables (age, gender, and race), variables related to the instant crime (commitment offense, age at prison admission, sentence length, etc.) and criminal history variables if available (prior arrests, type of crime charged at arrest, and age at first arrest). While the study represented an important step forward in the examination of the effectiveness of prison-based college programs, they did not have any control over the depth of the data they were given to analyze.

In contrast, the current study was able to access a fairly rich set of data in order to examine the effectiveness of prison-based college education programs in New York State. One of the major challenges in estimating the program’s effect on participants is dealing with the problem of selection bias which is an inherent concern with this type of data. In essence, prisoners who have a high level of motivation and self-control are likely to self-select themselves into prison-based college programs. Comparing recidivism outcomes between those who participated in and completed such programs and those who did not would therefore be biased.

In the current study, we have set out to address selection bias in estimating the impact of prison-based college education attainment on recidivism by using a propensity score matching (PSM) technique. Given the richness of our data, we used 49 variables reflecting socio-demographic factors, mental health or academic ability, criminal history, and current crime and sentence information. Based on a variety of offender characteristics, we estimate a binary model predicting the status of program participation and calculate propensity scores by which to pair prisoners who completed prison-based college education and prisoners who did not. We then test two main hypotheses on recidivism outcomes: (1) prison-based college education will decrease the probability of criminal recidivism and (2) the hazards of recidivism over time will be lower for those who completed a prison-based college program (treatment group) than those who did not (matched comparison group).

**Data and sample**

We examine the effect of prison-based college programs on recidivism by analyzing criminal history data obtained from the New York State Division of Criminal Justice Services (DCJS) and prison data from the New York State Department of Corrections and Community Supervision (NYS DOCCS). Prison data include, but are not limited to, demographic and socioeconomic characteristics, the instant crime and sentencing information, and academic information prior to admission into NYS DOCCS custody and during incarceration.

Our study is limited to prisoners who were first-released from NYS DOCCS to the community between calendar years 2005 and 2008. This includes discharges from New York State correctional facilities for (1) the expiration of a sentence, (2) releases by the decision of the parole board, or (3) conditional releases. This study excludes offenders who were released for deportation, medical releases (e.g., temporary release to a mental health facility and death), and civil commitments for sex offenses. As they cannot, by definition, have a recidivating event, the inclusion of such cases in analysis could yield misleading results. Also excluded are offenders who did not have a high-school diploma (HSD) or a High School Equivalency (HSE) status at admission and did not earn such a diploma while incarcerated because they are academic pre-requisites for admission into the prison-based college education program. Lastly, those who held a valid one-year college certificate or higher college degree at admission are excluded because the purpose of this study is to understand how prison-based college education attainment can help prisoners maintain a law-abiding life once released.

There were 31,815 cases available for the initial analysis. Of these, 347 offenders earned a one-year college certificate or higher degree while incarcerated and 30,838 offenders were eligible to participate in a prison-based college program but did not participate before they were release from prison.

We utilized PSM for constructing a comparison group. Data used for the PSM procedure in this study are quite rich, yielding the satisfactory performance of matching. The number of covariates used in PSM was extensive and so was the size of a comparison pool from which to draw matched controls. After constructing a matched dataset through PSM, the final sample size of this study became 680 including 340 offenders who earned a one-year college certificate or higher degree while incarcerated and their matching counter-parts. The PSM procedures and results will be discussed in more detail later below.

**Measures**

**Recidivism**

Recidivism is measured by any arrest for a crime occurring within three years of release. It is possible that one could be arrested after...
release from prison for a crime that was committed prior to the offender’s state incarceration. For example, an offender can be convicted years after he or she committed a crime as the result of newly discovered evidence. The occurrence date of crime was tracked for all recidivism events (e.g., arrests), and such arrests were removed from data analysis. The recidivism outcome is a dichotomous indicator coded 0 for those who were not re-arrested within three years of release and 1 for those who were re-arrested within three years of release.

**Prison-based college education (Treatment)**

Treatment defined and operationalized in this study is earning a college degree in prison. The treatment group consists of those who did not hold any college degree when admitted to prison but earned one prior to release. The college degree in this study includes a one-year college certificate, an associate’s degree, or a bachelor’s degree. The comparison group consists of those who held a HSD or HSE before release but have not taken a college program while incarcerated.

**Covariates**

The PSM procedure used 49 variables that can be classified into major domains: (1) socio-demographic factors, (2) mental health or academic ability, (3) criminal history, and (4) current crime and sentence information. These covariates capture the characteristics of prisoners prior to treatment (receiving college programs). Table 1 provides a description and descriptive statistics of the covariates used in this study.

**Socio-demographic factors**

These covariates include gender, race, age at admission, marital status, the number of living children, citizenship, and employment and military history before admission. The proportion of females in the study sample is very small. This is similar to the general population of female offenders who were released from NYS prisons. We also conducted the analysis including male offenders only, and the results were consistent.

**Mental health and academic ability**

The second set of covariates concerns whether or not an offender is eligible to participate in a prison-based college program. Since the presence of a behavioral or cognitive problem may disqualify prisoners from eligibility for educational programs, we assessed the mental health condition of prisoners at admission. In addition, we captured the level of academic ability through reading and math test scores and IQ test scores. Whether an inmate earned a high school equivalency (HSE) in prison or earned it in the community was also included. Finally, the number of college eligible days is included. Prisoners must have enough time left to serve on their sentence to complete a prison-based college program prior to their release. The beginning of college eligible days began from admission date for those who had a HSD/HSE before admission, and from the date of earning a HSE for those who earned the degree in prison.

**Criminal history**

The following variables were measured to capture the extent of criminal history prior to admission to prison: (a) the total number of prior convictions, (b) the different types of prior convictions including felony, misdemeanor, drug, robbery, assault, and sex offenses, (c) the age of the offender at first arrest, and (d) the most recent prior sentence type (0 = all others, 1 = jail or prison incarceration).

**Current crime and sentence information**

Lastly, we included measures concerning an instant offense for which prisoners were convicted and its sentencing outcomes. This information consists of (a) the type of the most serious conviction offense (as determined by sentence length), (b) verdict type (plea or jury conviction), (c) sex offender indicator, (d) aggregate minimum and maximum sentence length, and (e) commitment type.10

**Additional measures for a matched sample analysis**

Once the construction of matched comparison units was complete through PSM, we conducted subsequent analyses on the probability of recidivism and the time to recidivism. In addition to the treatment indicator, a few variables of theoretical importance were included in the subsequent analyses for additional control. Included are demographic variables (gender and race) and criminal history variables of age at first arrest and felony offender status. Criminal history variables are closely related to the risk of recidivism (e.g., Steurer et al., 2001; Winterfield et al., 2009). Also included are release-related variables such as age at release, total time served, and release type. These variables were not included in the PSM method because the covariates in the PSM method should be measured temporally prior to the treatment (Apel & Sweeten, 2010). Since the release-related variables were measured after inmates completed college programs in prison (post-treatment), they were not included in the matching procedure but were included in regression models due to their possible relationship with recidivism. The average age at release of sample members is 44. This is almost ten years older than the general population. Considering that people tend to age out of crime as they get older, the recidivism rates of the study sample members are expected to be lower than those of the general population of the releasees from NYS prisons. Of the 680 sample members, 61 percent were released by the Board of Parole, 38 percent were conditional releases, and only eight offenders (six from the treatment group and two from the matched group) were released after serving their maximum sentence. Those who were released by the Board of Parole were coded as one and the others were coded zero. Lastly, we measured the time to re-arrest in days for use in a Cox regression model to examine the risk of event occurrence (re-arrest). Someone arrested immediately after release from prison would have a higher propensity toward criminal behavior than someone arrested much later. Therefore, we took the length of time remained in the community into consideration and conducted a survival analysis. The descriptive statistics of the additional variables are presented in Table 2.

**Methods**

**Propensity Score Matching**

One of the main purposes in evaluation studies is to learn whether or not a program of interest yields an expected impact on program participants, and in most cases, a randomized experimental design is the preferred means of studying the effectiveness of the program. However, an experimental design is often difficult to implement and especially impractical for highly vulnerable populations such as prisoners. As such, program outcomes in such settings are often evaluated with quasi-experimental designs and observational data.

Selection bias can be a significant threat to internal validity in observational studies. For example, program outcomes can be influenced by some characteristics of program participants that are absent in the group of non-participants at the beginning of program admission. In other words, comparing the average values of outcomes between two groups may produce biased results because the selection process into the treatment can be influenced by other factors. Without controlling for the confounding factors that may influence both treatment and outcomes, one cannot be sure that the actual impact of treatment will be measured (Bifulco, 2002; Campbell & Stanley, 1966).

There are a few quasi-experimental techniques that create a situation where inclusion in the treatment group could be as good as a random assignment (see Apel & Sweeten, 2010; Morgan & Winship,
Of the available alternative methods to experimental designs, PSM has become widely popular and applicable to the evaluation of numerous criminal justice interventions. The propensity score is the conditional probability of selecting treatment given observed covariates (Morgan & Harding, 2006; Rosenbaum & Rubin, 1983). Rather than exercising physical control over the treatment conditions as is the case in the randomized environment, we can exercise statistical control over the conditions by selecting a group that has similar characteristics to the treatment group (Apel & Sweeten, 2010). In other words, we can find a group of offenders who have not earned a college degree but seem to have similar characteristics to those who earned a degree while incarcerated. The group developed in this way becomes a counterfactual for the treatment group, and this may allow us to measure the unbiased treatment effect. In this study, we utilized a one-to-one nearest neighbor matching method with replacement and within a caliper of 0.12.

### Table 1

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Treatment</th>
<th>Matched Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recidivism arrest within 3 years of release for crime committed after release (0 = no, 1 = yes)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment (Prison Collg.)</td>
<td>Completing college education before release (0 = no college education, 1 = received 1 year college certificate, associate degree, or bachelor's degree)</td>
<td></td>
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</tbody>
</table>

#### Sociodemographic

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment Mean S.D.</th>
<th>Matched Comparison Mean S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender 1 = male, 2 = female</td>
<td>1.068 0.252</td>
<td>1.053 0.224</td>
</tr>
<tr>
<td>White 0 = non-white, 1 = white</td>
<td>0.221 0.415</td>
<td>0.197 0.398</td>
</tr>
<tr>
<td>Age at admission</td>
<td>30.337 7.773</td>
<td>31.446 8.637</td>
</tr>
<tr>
<td>English speaking Whether or not speaking English</td>
<td>0.962 0.192</td>
<td>0.947 0.224</td>
</tr>
<tr>
<td>Number of children The number of living children</td>
<td>0.729 1.549</td>
<td>0.871 1.695</td>
</tr>
<tr>
<td>Marital Status Marriage Status (0 = not married, 1 = married or common-law married)</td>
<td>0.418 0.494</td>
<td>0.450 0.498</td>
</tr>
<tr>
<td>Employment Employment before admission (0 = no job, 1 = had a job)</td>
<td>0.588 0.493</td>
<td>0.624 0.485</td>
</tr>
<tr>
<td>Citizenship Citizenship (0 = non-US citizen, 1 = US citizen)</td>
<td>0.912 0.284</td>
<td>0.897 0.304</td>
</tr>
<tr>
<td>Military 0 = no military 1 = served in military before admission</td>
<td>0.147 0.355</td>
<td>0.150 0.338</td>
</tr>
</tbody>
</table>

#### Mental/Academic Ability

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment Mean S.D.</th>
<th>Matched Comparison Mean S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alcoholic indicator Alcoholic indicator (0 = no, 1 = alcoholic)</td>
<td>0.162 0.369</td>
<td>0.126 0.333</td>
</tr>
<tr>
<td>OMH level Mental health level</td>
<td>6.094 1.256</td>
<td>6.188 1.197</td>
</tr>
<tr>
<td>Reading level Reading level</td>
<td>11.114 2.433</td>
<td>11.121 2.429</td>
</tr>
<tr>
<td>Math level Math level</td>
<td>10.339 2.853</td>
<td>10.139 2.956</td>
</tr>
<tr>
<td>HSE in prison To receive HSE in prison (0 = no, 1 = yes)</td>
<td>0.347 0.477</td>
<td>0.291 0.455</td>
</tr>
<tr>
<td>IQ Intelligence level</td>
<td>67.762 49.550</td>
<td>71.188 46.635</td>
</tr>
</tbody>
</table>

#### College days Available days for college education | 199.003 85.881 | 199.850 101.736 |

#### Current crime

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment Mean S.D.</th>
<th>Matched Comparison Mean S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conviction Number of prior convictions</td>
<td>3.021 2.962</td>
<td>3.038 2.775</td>
</tr>
<tr>
<td>Felony Number of prior felony convictions</td>
<td>1.726 1.199</td>
<td>1.812 1.377</td>
</tr>
<tr>
<td>Misdemeanor Number of prior misdemeanor conviction</td>
<td>0.941 1.989</td>
<td>0.876 1.654</td>
</tr>
<tr>
<td>Prior VFO Number of prior violent felony offenses</td>
<td>1.218 0.882</td>
<td>1.300 0.977</td>
</tr>
<tr>
<td>Fel. drug Number of prior felony drug offenses</td>
<td>0.168 0.547</td>
<td>0.147 0.475</td>
</tr>
<tr>
<td>Misd. drug Number of prior misdemeanor drug offenses</td>
<td>0.150 0.659</td>
<td>0.100 0.596</td>
</tr>
<tr>
<td>Fel. weapon Number of prior felony weapon offenses</td>
<td>0.459 0.730</td>
<td>0.509 0.857</td>
</tr>
<tr>
<td>Misd. weapon Number of prior misdemeanor weapon offenses</td>
<td>0.050 0.218</td>
<td>0.053 0.237</td>
</tr>
<tr>
<td>Fel. Robbery Number of prior felony robbery</td>
<td>0.406 0.902</td>
<td>0.494 0.970</td>
</tr>
<tr>
<td>Fel. Assault Number of prior felony assault</td>
<td>0.082 0.306</td>
<td>0.094 0.312</td>
</tr>
<tr>
<td>Misd. Assault Number of prior misdemeanor assault</td>
<td>0.082 0.324</td>
<td>0.091 0.327</td>
</tr>
<tr>
<td>Fel. Sex offense Number of prior felony sex offenses</td>
<td>0.091 0.318</td>
<td>0.076 0.277</td>
</tr>
<tr>
<td>Misd. Sex offense Number of prior misdemeanor sex offenses</td>
<td>0.006 0.077</td>
<td>0.000 0.000</td>
</tr>
<tr>
<td>Fel. Burglary Number of prior felony burglary</td>
<td>0.168 0.547</td>
<td>0.218 0.674</td>
</tr>
<tr>
<td>Misd. Burglary Number of prior misdemeanor burglary</td>
<td>0.079 0.311</td>
<td>0.079 0.356</td>
</tr>
<tr>
<td>Fel. Escape Number of prior felony escape (custody related)</td>
<td>0.026 0.178</td>
<td>0.032 0.177</td>
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<tr>
<td>Misd. Escape Number of prior misdemeanor escape (custody related)</td>
<td>0.038 0.207</td>
<td>0.044 0.206</td>
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<tr>
<td>Fel. DUI Number of prior felony DUI</td>
<td>0.012 0.108</td>
<td>0.013 0.054</td>
</tr>
<tr>
<td>Misd. DUI Number of prior misdemeanor DUI</td>
<td>0.018 0.132</td>
<td>0.012 0.168</td>
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<tr>
<td>Fel. Property Number of prior felony property crime</td>
<td>0.059 0.259</td>
<td>0.062 0.325</td>
</tr>
<tr>
<td>Misd. Property Number of prior misdemeanor property crime</td>
<td>0.365 1.011</td>
<td>0.374 0.974</td>
</tr>
<tr>
<td>Arrest age Age at first arrest</td>
<td>20.532 5.672</td>
<td>21.244 6.066</td>
</tr>
<tr>
<td>Sentence Most recent prior sentence (0 = all others, 1 = jail/prison)</td>
<td>0.653 0.477</td>
<td>0.585 0.493</td>
</tr>
</tbody>
</table>

#### Recidivism: Arrest within 3 years of release for crime committed after release (0 = no, 1 = yes)

#### Treatment

2007; Nichols, 2007). Of the available alternative methods to experimental designs, PSM has become widely popular and applicable to the evaluation of numerous criminal justice interventions. The propensity score is the conditional probability of selecting treatment given observed covariates (Morgan & Harding, 2006; Rosenbaum & Rubin, 1983). Rather than exercising physical control over the treatment conditions as is the case in the randomized environment, we can exercise statistical control over the conditions by selecting a group that has similar characteristics to the treatment group (Apel & Sweeten, 2010). In other words, we can find a group of offenders who have not earned a college degree but seem to have similar characteristics to those who earned a degree while incarcerated. The group developed in this way becomes a counterfactual for the treatment group, and this may allow us to measure the unbiased treatment effect. In this study, we utilized a one-to-one nearest neighbor matching method with replacement and within a caliper of 0.12.
By allowing for untreated units to be used more than once in the matching procedure, this specification produces smaller matching discrepancies than matching without replacement.

**Conditional (Fixed-effects) logistic regression model**

To measure the probability of recidivism within three years of release, we used a conditional (also called fixed-effects) logistic regression for a matched sample (see Hosmer & Lemeshow, 2000; McFadden, 1974). The conditional logistic regression model differs from regular logistic model in that the data are grouped and the results are based on each group (see StataCorp, 2011, p. 271). Each matched pair of sample members selected by the PSM method, one with treatment and another with no treatment, is identified as a group. Conditional likelihood on the binary outcome for each group includes cases for which outcomes vary between two individuals within a group. If the outcomes are the same (both are zero or one’s), it effectively eliminates the group from the analysis. In other words, if both offenders within a group were re-arrested (or not re-arrested), they would not be included in the analysis because there is no change in the outcome.

**Proportional hazards model (Cox regression)**

We further analyzed the impact of prison-based college education on recidivism by employing a survival analysis method. Results from the logistic model have the advantage of yielding straightforward interpretations, but do not control for the amount of at-risk time each individual had while in the community. Further, the timing of re-arrest is of substantive interest to the current study. Thus, we took the length of at-risk time into consideration and conducted a survival analysis. Similar to the conditional logistic regression model, the sample members matched using the PSM method were analyzed in the proportional hazard ratio model that addresses the question of how quickly the treatment and matched comparison groups recidivated after release from prison (see Cox, 1972).

**Findings**

**Matching results**

First, we conducted t-tests to determine the equivalence of the treatment and matched comparison groups. Before matching, there were significant differences in most background factors between prisoners who achieved a college degree and prisoners without college experience. Compared to prisoners released from prison without having college experience, for example, prisoners who earned a college degree were admitted to prison at younger ages, tended to be employed and have served in military before admission, had generally fewer convictions prior to admission to prison, and had received a longer sentence. After matching, the two groups became equivalent on all covariates examined.

Fig. 1 graphically shows how well the data have been balanced after matching. It displays the standardized percentage bias for each covariate (see Rosenbaum & Rubin, 1985; StataCorp, 2011). Solid dots represent bias before matching and x marks represent bias after matching. As can be seen, unmatched data show large bias on most variables, whereas the matched data show all variables with almost zero standardized bias. It should also be noted that the overall bias has been significantly decreased after matching.

Table 3 shows the average treatment effects of prison-based college programs on three different recidivism intervals before and after matching. The first set of rows show the recidivism rate within one year of release. Before matching, the average recidivism rate within one year of release was significantly higher for a comparison group (9.5%) than for a treatment group (2.3%), but the differences get substantially smaller after matching. After matching, the difference is only 1.5% and appears to be no longer statistically significant. If the PSM method was not used, one would have concluded that the completing college education in prison significantly reduce re-arrest rates within one year of release. The results of two year recidivism intervals are similar. The differences in the recidivism rates are 19.0% before matching and 4.7% after matching. Although the difference is still statistically insignificant, the significance level is improved (t-stat. = – 1.77).

The last rows in the table show the recidivism rates within three years of release. Without PSM matching (before matching), the average recidivism rate for those who did not take college education was 35.9 percent, substantially higher than the recidivism rate for college-degree achievers (9.5 percent). After matching, the recidivism rate of the non-college participants decreased substantially. This indicates that non-random selection into treatment was substantial and that the effect of prison-based college programs on recidivism would be markedly overestimated without addressing selection bias. The recidivism rate for the matched control group is 17.1 percent.

![Distribution of Bias](image)

**Table 3**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample</th>
<th>Treatment</th>
<th>Comparison</th>
<th>Diff.</th>
<th>S.E.</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least 1</td>
<td>Before Matching</td>
<td>0.023</td>
<td>0.095</td>
<td>-0.072</td>
<td>0.016</td>
<td>-4.25</td>
</tr>
<tr>
<td></td>
<td>After Matching</td>
<td>0.024</td>
<td>0.038</td>
<td>-0.015</td>
<td>0.017</td>
<td>-0.87</td>
</tr>
<tr>
<td>Least 2</td>
<td>Before Matching</td>
<td>0.058</td>
<td>0.247</td>
<td>-0.190</td>
<td>0.023</td>
<td>-8.17</td>
</tr>
<tr>
<td></td>
<td>After Matching</td>
<td>0.059</td>
<td>0.106</td>
<td>-0.047</td>
<td>0.027</td>
<td>-1.77</td>
</tr>
<tr>
<td>Least 3</td>
<td>Before Matching</td>
<td>0.095</td>
<td>0.359</td>
<td>-0.264</td>
<td>0.026</td>
<td>-10.22</td>
</tr>
<tr>
<td></td>
<td>After Matching</td>
<td>0.094</td>
<td>0.171</td>
<td>-0.076</td>
<td>0.032</td>
<td>-2.36</td>
</tr>
</tbody>
</table>
and 9.4 percent for the treatment group. Although the difference in the recidivism rates between two groups decreases from 26.4 percent to 7.6 percent, the difference is still statistically significant. This suggests that prison-based college education significantly reduces recidivism apart from a released prisoner’s inclination to avoid criminal behavior once returned to the community.

In summary, the results show that the recidivism rate of the comparison group decreased substantially after matching. Yet, offenders who completed college programs in prison show lower recidivism rates within three years of release compared to their matched comparison group. Although the differences in the treatment effects between two groups are statistically insignificant in one and two year recidivism intervals, they show patterns similar to the results of the three year follow-up. This may suggest that the length of follow-up time matters. The average recidivism rates of offenders who are eligible to take college courses or complete college programs would be much lower than the general offender population. Thus, short follow-up periods would not provide enough recidivism cases to test substantial differences between treatment and control groups, and three years of release to the community seem to provide a long enough period of time for everybody to have a chance to recidivate or not.

Conditional (Fixed-effects) logistic regression models

Table 4 shows the results of conditional logistic regression models. With additional covariates controlled, the conditional logistic models produce more precise estimates for program impact. The results are consistent with those from Table 3. The treatment (earning a college degree in prison) has a positive effect on reducing recidivism. While controlling for the possible unobserved heterogeneity through fixed effects, earning a college degree in prison decreases the odds of recidivism by 54.2 percent. This is supporting evidence for the positive impact of prison-based college programs on offender’s rehabilitation.

One may notice that all other variables except for the treatment are insignificant in the conditional logistic regression model. This would be because the fixed effects model uses within-group variation. Since two individuals within a group are supposed to be the same because they were the paired by the PSM method, there is little variation in such variables that explain the outcome. The only difference should be whether someone received treatment or not. Thus, if the matching process has been done properly, there would be no variation in other observed covariates, and thus one would expect to see the effects be zero.

While the conditional regression shows the likelihood of recidivism if an offender completes college education in prison and has the advantage of being a reasonably straightforward method, it has the disadvantage of wasting ‘timing’ information (the length of time between release from prison and the time of first recidivism). Therefore, we employed a Cox regression to measure the risk of recidivism over time.

Proportional hazard models (Cox regression)

Similar to the fixed effects model, the matched sample is used for a Cox regression. Results from the Cox regression model are presented in Table 5. The model includes a treatment variable, indicating whether or not a prisoner earned a college degree, demographic variables, and other variables mostly related to release status. We first tested whether the data satisfy the proportional hazards assumption that the ratio of hazards is a constant, and found that the model was adequate and covariates do not have different effects at different points in time (see Schoenfeld, 1982).

Consistent with the earlier analyses, the model indicates that earning a college degree in prison decreases the risk of recidivism (re-arrest) by nearly 50 percent while holding other covariates constant. The risk of recidivism over time is greater among the matched comparison group (offenders with no college experience in prison) than among the treatment group (offenders who earned a college degree in prison). For those who have not recidivated after three years of release, their survival rate is nearly 93 percent for the treatment group and 87 percent for the matched comparison group (see Fig. 2). It is worth mentioning that the hazards of recidivism were quite low for both groups, compared to the general prisoner population, but the treatment group even showed lower rates of re-arrest than the matched comparison group.

Besides the treatment variable, four of the covariates are significant in the Cox regression equation, whereas none of the seven covariates have statistically significant effects in the conditional logistic model. As explained earlier, this may be because the conditional logistic model uses within-group variation and matched pairs share the same characteristics. Thus, there is not much within-group variation in the covariates except for the treatment variable that explains

<table>
<thead>
<tr>
<th>Hazard Ratio</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment (0 = comparison, 1 = treatment)</td>
<td>0.525**</td>
</tr>
<tr>
<td>Age at Release</td>
<td>1.007</td>
</tr>
<tr>
<td>Time served</td>
<td>0.994**</td>
</tr>
<tr>
<td>Release type</td>
<td>1.726*</td>
</tr>
<tr>
<td>Fel. offender status</td>
<td>2.789**</td>
</tr>
<tr>
<td>Age at 1st Arrest</td>
<td>0.906**</td>
</tr>
<tr>
<td>Sex</td>
<td>0.444</td>
</tr>
<tr>
<td>White</td>
<td>0.887</td>
</tr>
</tbody>
</table>

* P < 0.05 ** p < 0.01

LR chi^2(8) = 85.96 (p < .001)
the outcome. Another explanation could be that the conditional logis-
tic model drops matched pairs with identical outcomes, and thus
generates a smaller sample size and larger standard errors in the lo-
gistic equation than in the Cox equation.

In summary, we find that prison-based college education can ef-
effectively reduce recidivism. The different modeling approaches used
in this study show consistently positive results. When an offender
completes a prison-based college program while incarcerated, he or
she would be significantly less likely to recidivate after release. Fur-
thermore, those who earned a college degree while incarcerated
stay crime-free in the community longer than those who did not par-
ticipate in college programs.

Discussion and conclusion

The goal of this study was to examine the effect of prison-based
college education on recidivism by employing a statistically robust
methodology. As noted above, a review of the existing prison educa-
tion research literature found that many studies were limited to cor-
relation analysis or simple descriptive comparisons of return rates.
This discovery raised significant questions about the effect weak re-
search designs may have had on the validity of interpretations of
study findings. Moreover, these methodological shortcomings pre-
cluded any possibility of testing the causal relationship between
prison-based college education and recidivism.

While a randomized controlled trial was not possible, this study
employed a Propensity Score Matching technique to identify a valid con-
trol group that shares similar background characteristics with offenders
who successfully completed college programs while incarcerated. By
comparing pre- and post- matching results, the current study showed
that the effect of prison-based college programs could be inflated with-
out properly controlling for self-selection bias. A pre-PSM analysis indi-
cated that offenders who did not participate in college programs had a
re-arrest rate of 35.9% that is 3.8 times higher than the return rate
(9.5%) of offenders who successfully completed prison-based programs.
After applying a PSM method, the re-arrest rate of the control
group (no college) decreased to 17.1% which is only 1.8 times higher
than the return rate of the treatment group (9.4%).

While controlling for selection bias, our study shows that
prison-based college education effectively lowers recidivism. Further analyses of the effect of prison-based college programs confirmed
that the treatment was effective. The result of conditional logistic re-
gression analysis showed that the probability of recidivism decreases
when an offender earned a college degree compared to when his or
her matched counterpart did not participate in college programs. In
addition, the risk of recidivism over time was also smaller among
the treatment group than among the control group. Thus, one can
conclude that completing prison-based college programs has a posi-
tive effect on reducing recidivism.

Establishing that prison-based college programs reduce recidivism
answers the substantive question of whether the program can affect
crime and incarceration rates. However, at the end of the day, correc-
tional programs are a product of public policy and as discussed in the
opening paragraphs of this study, correctional education policy is a
product of both ideological and pragmatic arguments by both the pri-
ivate and public spheres. While private sector groups or organizations
may be more inclined to justify the provision of prison-based college
education on ideological or humanitarian grounds (see Fine et al.,
2001; Hower, 2012), public-policy makers have to focus on the tangi-
ble or pragmatic aspects of providing a free service to a population of
convicted offenders that is not similarly provided to the law-abiding
population. Toward this end, Aos, Miller, and Drake (2006b) focused
on an economic justification by estimating the economic benefits as-
associated with evidence-based programs. They state that achieving
the threshold of a seven percent reduction in recidivism can result in cost
savings for both taxpayers and crime victims. For example, their
estimates suggest that general education programs in prison (includ-
ing basic education and postsecondary) can save over $5,000 per of-
fender and a corresponding cost-saving estimate of over $6,000 per
crime victim. Our study showed that the college program reduced the
recidivism rate by over 7 percent, and thus should benefit tax-
payers, crime victims, and offenders.

Regardless of one’s ideological position on prison-based college
education programs the literature consistently suggests that such
programs are related to lower levels of recidivism in the participant
population. Our research represents a more methodologically rigor-
ous research design that continues to affirm the positive effect of
prison-based college educational programs widely reported through-
out the correctional education literature albeit at a less inflated level
than that produced by less rigorous designs. And, in light of the re-
search conducted by Aos et al. (2006b) there would appear to be a
pragmatic justification for including prison-based college education
in correctional programming.

Acknowledgements

The authors wish to express their deep appreciation to Linda
Hollmen, KiDeuk Kim, Paul Korotkin, Alan Lizotte, and David McDowall
for their valuable comments and suggestions on earlier drafts of this paper.

Notes

1. According to Inglis (1918), there are three aims of the American secondary
school system. First, the social-civic aim of education is to prepare the individual
to be a cooperative member of society and to inculcate in that individual a sense of civic
duty. While moral education was seen as a primary mission of public education in the early
20th Century (Dewey, 1914; Roosevelt, 1930), the role of moral education in public
schools went largely out of favor at the end of World War II (McCellan,
1999). The second aim is the economic-vocational aim that is to produce social unity
in an increasingly diverse population in the most efficient and cost effective way pos-
sible. In the early 20th Century the public school system expanded its goals to include
preparation of students for entry into the workforce (Gordon, 1999). The third aim is
the individualistic-avocational aim that stresses the acquisition of knowledge to be-
come wise and enlightened. The study of literature, science, mathematics, art, and phi-
losophy is designed to produce an understanding of human nature, morality, and what
constitutes a good life (Dillon, 2004). There are also those who take a non-instrumental
view of education in which learning is an end in itself (Su, 2001). Like moral education,
however, the educational aim of learning to become wise and enlightened has also di-
iminished in the American system of higher education (Nguyen, 2000).

2. See Federal Pell Grant description published by the U.S. Department of Educa-
tion (http://www2.ed.gov/programs/pfg/index.html).

3. When the Violent Crime Control and Law Enforcement Act of 1994 was enacted
in the early years of the Clinton Administration, it contained a provision that banned
offenders from obtaining Pell Grants. In 1998, however, Public Law 105-244 amended
the Higher Education Act of 1965 and established a grant program for incarcerated
youth in state prisons. Congress chose not to fund the program for federal fiscal year
2011-2012.

4. The education policy is explained Directive 4804 ‘Academic education program

5. PSCE in the study refers to any type of education beyond high school (or its
equivalency) that has inmates of prisons or jails for students: vocational, academic, un-
dergraduate, graduated, certificate and/or degree programs.

6. Conditional release is required by statute (New York Penal Law § 704). As long
as a prisoner’s maximum term is not life-imprisonment, the prisoner can be released
on a conditional release date by earning a ‘good time credit’ that is up to one-
seventh of a determinate sentence or one-third of an indeterminate sentence (New
York Correction Law § 803). Four months prior to a prisoner’s conditional release date
an administrative review is conducted by a facility-based Time Allowance Committee
to determine if that prisoner has lost any good time during their incarceration as the
result of prison rule violations.

7. Seven treated cases were not matched to an equivalent comparison unit and
were therefore removed from analysis.

8. It is plausible to posit that different levels of educational attainment can yield
different effect sizes. The current approach, however, does not allow for the estimation
of heterogeneous treatment effects. Thus, combining the different levels of educational
attainment in one treatment module is a potential limitation in this study despite the
fact that it yields an intuitive interpretation of program impact for policy and practice.

9. In 2010, only seven percent of first releases from NYS prisons were female (see
Kim, 2011).

10. The commitment type is a dichotomous variable. Those who committed a new
crime on the street (under no parole supervision) are coded 1. All other cases including
parole or conditional release violators who committed a new crime and received new
term are coded 0.
11. The average age of prisoners first released to the community is around 35 (see Kim, 2011).

12. Common support between treatment and comparison groups is important in PSM, and the caliper determines the number of off-support cases to be included in the treatment effect estimates (Apel & Sweeten, 2010). Restricting the caliper to a smaller size produces closer matches but reduces the sample size. To test sensitivity, we had additional analyses using various calipers from 0.01 to 0.05 and had consistent results with respect to the estimated treatment effect and significance of the effect.

13. A fixed effects logistic model uses within-group variation not between-group variation. If the predictor variable had little variation, it would have a large standard error and be less efficient than other traditional methods. Yet, when there is much variation within a group, fixed effects models would be preferred to others. Since fixed effects regression models help control for unobserved variables, the results would be less biased than other methods (see Allison, 2009).

14. If one chose to do a one-tail test, the difference is statistically significant at .05 level.

15. Approximately 20 percent of re-arrestees from each group were arrested for violent felony offense (19.0 percent for the treatment and 21.9 percent for the control level.

16. The marginal effect on the probability at the mean of the outcome (0.132) is -0.090. In other words, completing a college degree reduces probability of recidivism by n=percentage points.

17. The test was based on Schoenfeld residuals using various functions of time (i.e. default time, Kaplan-Meier, log, and rank) and the results consistently indicated that there was no evidence to violate the assumption.

18. 0.525-1 = -0.475.

References