

The Impact Evaluation of the Maryland Break the Cycle Initiative

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EXECUTIVE SUMMARY

OVERVIEW

This evaluation examined the impact of Break the Cycle (BTC), an initiative designed to reduce drug use and crime among probationers and parolees in the state of Maryland. The BTC strategy uses intensive supervision to encourage offenders on supervision to abstain from using drugs and participate in drug treatment. BTC was adopted by the Division of Parole and Probation (DPP) for all offenders under DPP who were under supervision with a drug condition stipulated by a judge or the Parole Commission. Efforts to increase access to drug treatment took place in many DPP offices across the state and supervising agents were encouraged to apply sanctions for violations of drug conditions. Six of Maryland's largest counties (Baltimore, Charles, Howard, Montgomery, Prince George's, and Washington) and Baltimore City received additional funds from the Maryland Legislature to support the implementation of BTC. These funds were used primarily for additional drug testing. In addition, these BTC areas developed a data system (HATS) to support the monitoring and treatment referral process for eligible probationers and parolees.

The yardstick used to measure the impact of BTC was reduction in the likelihood and number of arrests of probationers and parolees in the year after starting supervision. Only arrests that result in new charges being filed are included.¹ Arrest measures include an arrest for any offense and an arrest for a drug offense. Using data from existing computer systems, the evaluation design compares arrest of parolees and probationers in the BTC areas that received funding to arrests of similar offenders in seven non-BTC counties: Anne Arundel, Carroll, Cecil, Harford, Frederick, St. Mary's, and Wicomico. Extensive statistical controls were used in the analysis to adjust for differences in the counties and in the characteristics of individuals supervised by DPP in those areas.

The findings indicate that arrests of probationers and parolees with drug conditions were lower as a result of BTC as follows:

- Probationers and parolees with drug conditions had a slightly, but significantly lower likelihood of arrest for a drug offense and significantly fewer drug arrests;
- In BTC areas that administered more drug tests per person under supervision, probationers and parolees with drug conditions had a significantly lower likelihood of

¹ Revocations of parole or probation based on technical violations of conditions are not included, nor are arrest charges that are dropped.

arrest (for any offense and for drug offenses) and significantly fewer arrests (for any offense and for drug offenses); and

- In BTC areas that administered more sanctions (immediate penalties for infraction of drug condition requirements) per person under supervision, probationers and parolees with drug conditions had slightly, but significantly lower likelihood of arrest (for any offense and for drug offenses) and significantly fewer arrests for drug offenses.

We did not find significant reductions in arrest among all offenders, nor were reductions in arrest associated with the ratio of sanctions to positive drug tests.

We interpret these results to mean that BTC is an effective strategy for reducing drug arrests among probationers and parolees with drug conditions. The BTC areas that used more drug testing and sanctions in response to infractions of drug conditions experienced greater reductions in new offenses. This suggests that the magnitude of the reductions could be increased by more widespread use of these strategies. One factor that could not be measured by this evaluation was whether BTC increased participation in drug treatment and what role drug treatment played in producing the observed outcomes.

These results are consistent with a growing body of literature that indicates the effectiveness of combining intensive drug testing, sanctioning and drug treatment. The national evaluation of the Breaking the Cycle Demonstration in Birmingham, AL, Jacksonville, FL, and Pierce County, WA, Compared felony defendants who did and did not receive BTC services. It found:

- Statistically significant reductions in drug use among BTC participants in two of three cities studied;
- Statistically significant reductions in self-reported offending, particularly in drug sales and possession, among BTC participants in all three cities;
- Statistically significant reductions in the likelihood of arrest in the following year among BTC participants in two of three cities studied; and
- Statistically significant reductions in family problems among BTC participants in all three cities (Harrell, Mitchell, Merrill, and Marlowe, 2002).

The analysis of costs and benefits found positive returns to the investment in the BTC demonstration in all three sites, ranging from \$2.30 to \$5.70 for each dollar invested. Not all of these savings could be readily converted into budget dollars for the agencies participating in BTC since they represent savings to a host of stakeholders including potential victims, public jurisdictions, insurers, citizens in general as well as the public law enforcement, courts and corrections systems. However, the benefits were consistent with the public safety, health, and welfare missions of the investing agencies.

Other studies have found that sanctions and drug treatment are effective in reducing crime and work best in combination:

- Falkin’s evaluation of community-based treatment for offenders found that treatment combined with urinalysis and court monitoring with sanctions had higher rates of success than treatment alone (Falkin, 1993).
- The evaluation of the DC Superior Court Drug Intervention program found reductions in drug use prior to sentencing and crime in the year after sentencing among program participants. A greater reduction in arrest was found among those who participated in NA/AA treatment (Harrell, Cavanagh, and Roman, 1999).
- The evaluation of Intensive Supervision Programs (ISP) found that combined treatment with strict surveillance reduced recidivism by as much as 15 percent over high levels of surveillance alone (Petersilia and Turner, 1993; Petersilia, Turner and Deschenes, 1992).

LIMITATIONS

The strength of the findings of BTC impact may be limited because the implementation of the core strategies was not strong across all BTC counties in the full post-BTC time period. The process evaluation of BTC indicates that the program was only partially in place at the end of 2001 (Taxman, Reedy, Moline, Ormand, and Yancey, 2003). However, BTC implementation showed continuing improvement, much of which occurred at the end of (or following) the Urban Institute’s study period. It will be important to the continued development of BTC that process and impact evaluation continue as the program attains more complete application of the underlying principles behind drug intervention with probationers and parolees.

The evaluation findings must also be interpreted cautiously in light of the research design and data limitations. The evaluation was based on a retrospective quasi-experimental design that relied on statistical procedures to control for differences between BTC and non-BTC areas and offender populations. For example, the measure of need for drug intervention was limited to a drug condition imposed by the court or Parole Commission, initially or later, in response to a recommendation by the supervising officer. Prospective experimental evaluation of impact would provide much more data to use in measuring exposure to BTC services, individual differences in drug abuse severity, and a wider range of outcome measures including reductions in drug use.

The reliance on secondary data from existing computer systems means that the analysis is limited to the variables collected for other purposes. It would have been very helpful, for example, to have a measure of treatment utilization by offenders under supervision in both BTC and non-BTC areas since, conceptually, treatment is a core component of the strategy for reducing drug use. Data systems containing criminal history and corrections files are subject to

variation in data definitions and quality over time and locations. Because the HATS database was under development during the study period, data cleaning involved removing duplicate records and the assumption that missing information on sanctions was random across BTC counties.

Despite these limitations, the evidence suggests that reductions in arrest rates among offenders with drug conditions will occur when drug testing is widely used and accompanied by sanctions. These reductions in arrests on new charges reflect benefits to the community in averted criminal activity and can be expected to reduce future corrections costs.

MAIN FINDINGS REPORT

INTRODUCTION

In 1997, the State of Maryland launched a new approach for the supervision of the drug-addicted offender. This initiative, Break the Cycle (BTC), targeted offenders on probation or parole with a “drug condition” designated as a supervision requirement by a judge or the Parole Commission. The objective was to reduce drug use among probationers and parolees by combining intensive monitoring of drug use with increased access to drug treatment as needed. The strategies included frequent drug testing and use of immediate sanctions for violations of drug conditions in an effort to encourage abstinence and participation in treatment. In support of the BTC initiative, the Maryland Legislature provided special funding to six of Maryland’s largest counties (Baltimore, Charles, Howard, Montgomery, Prince George’s, and Washington) and Baltimore City. Most of these funds were used for additional drug testing.

The rationale for focusing on offender drug use is based upon a large body of research indicating a close link between drug use and crime. The relationship of crime and chronic hard-drug use has been well documented in the literature (Inciardi, et al., 1997; Miller and Gold, 1994). Chronically hard-drug-involved offenders have high rates of criminal activity, with the frequency and severity of criminal behavior rising and falling with the level of drug use (Anglin, Longshore and Turner, 1999). Drug addicts have been found to commit four to six times more crimes when actively using drugs than when they are not abusing narcotics, a pattern that is even more pronounced among habitual offenders (Vito, 1989:65).

The implementation of BTC required the Division of Parole and Probation (DPP) as well as the Maryland Parole Commission, the courts, the Alcohol and Drug Abuse Administration (ADAA) of the Department of Health and Mental Hygiene (DHMH), local health departments, and local law enforcement agencies to collaborate in revolutionary ways around the common goal of reducing drug use among offenders under the supervision of DPP. The task was formidable. The agencies had to build a system for sharing data, expand working relationships between criminal justice and treatment professionals and agencies, expand treatment options for the targeted population, and develop the capacity for drug testing large numbers of offenders.

In response to requests from the legislature for a report on the effectiveness of BTC, the Governor’s Office of Crime Control & Prevention (GOCCP) funded the Urban Institute to conduct an evaluation of the impact of BTC on recidivism. The study is based on a retrospective analysis of arrests among probationers and parolees entering supervision before and after BTC. Data for the study were provided by the Division of Parole and Probation of the Department of

Public Safety and Correctional Services; the Information Technology and Communication Division of the Department of Public Safety and Correctional Services; and the Bureau of Governmental Research at the University of Maryland. Additional data were retrieved from published results of the US Census of 2000 and Uniform Crime Reports. In this study, recidivism is measured by the likelihood of arrest and number of arrests for a new offense resulting in a new charge during the first year of supervision.

The evaluation found a relatively small, but statistically significant reduction in the likelihood of arrest for a drug offense and numbers of arrests for drug offenses among probationers and parolees with drug conditions in BTC areas compared to those in non-BTC areas. The reductions in arrest were more significant and larger in BTC areas that used more drug tests per offender on supervision. In these BTC areas, reductions in recidivism include a significantly lower likelihood of arrest and significantly fewer arrests (for any offense and for a drug offense). In addition, the likelihood of arrest and number of arrests (drug arrests only) were significantly lower in BTC areas that used more sanctions per offender as called for by BTC protocols than in other areas. No reductions in arrest were found among the full population of all probationers and parolees.

THE RESEARCH DESIGN

The evaluation is based on a quasi-experimental comparison of probationers and parolees in BTC and non-BTC counties in Maryland. The BTC counties received additional funds for expanded drug testing and developed a computer system, the HIDTA Automated Tracking System (HATS) to monitor test results, infractions of drug conditions, the use of sanctions, and treatment participation of probationers and parolees with drug conditions. The quasi-experimental comparisons focus on the differences in recidivism associated with these innovations.²

Because BTC counties differ as a group from the non-BTC counties in size, crime rates, and enforcement policies and offenders in BTC counties may differ as a group from those in non-BTC counties in criminal risk and drug involvement, the evaluation used a multi-level approach to estimate differences in outcomes for offenders in BTC areas from those in other areas. The analysis uses statistical techniques developed and widely used by educational researchers to assess the impact of classroom innovations delivered in widely varying schools (different in size, location, student-teacher ratio, etc.) to students of varying ability (intelligence, age, prior preparation) (Bryk and Raudenbush 1992). In educational studies, student performance in classrooms that receive a new program is compared to student performance in classrooms that

² Development of expanded treatment options and services for offenders on supervision with drug conditions was encouraged as part of the BTC initiative in all counties and may have brought about reductions in drug use and crime not captured in this evaluation. Data on county differences in the use of drug treatment by probationers and parolees before and after BTC implementation were not available. Thus, the evaluation cannot measure the effects of use of drug treatment on recidivism or the extent to which the combined use of treatment and the measured BTC strategies affected recidivism.

did not implement the innovation, controlling for school and student differences. In this evaluation, the recidivism among probationers and parolees in BTC counties is compared to recidivism in non-BTC counties, controlling for county and offender differences.

The design used data on probationers and parolees supervised before and after BTC, using statistical techniques to adjust for differences between BTC and non-BTC areas and offenders. This design is less powerful than one in which eligible offenders are randomly assigned to BTC or non-BTC supervision and then followed over time. However, an experimental comparison was precluded by several constraints. These included: 1) lack of a readily identifiable group to compare to BTC participants (BTC targeted all eligible offenders within BTC jurisdictions and BTC jurisdictions differ from those that did not receive the funds for drug testing), 2) time constraints (policy makers wanted the assessment within a relatively short period of time), and 3) limited funds for research. The results depend, therefore, on the adequacy of the controls for differences between BTC and non-BTC areas and individuals under supervision in these areas.

THE SAMPLE

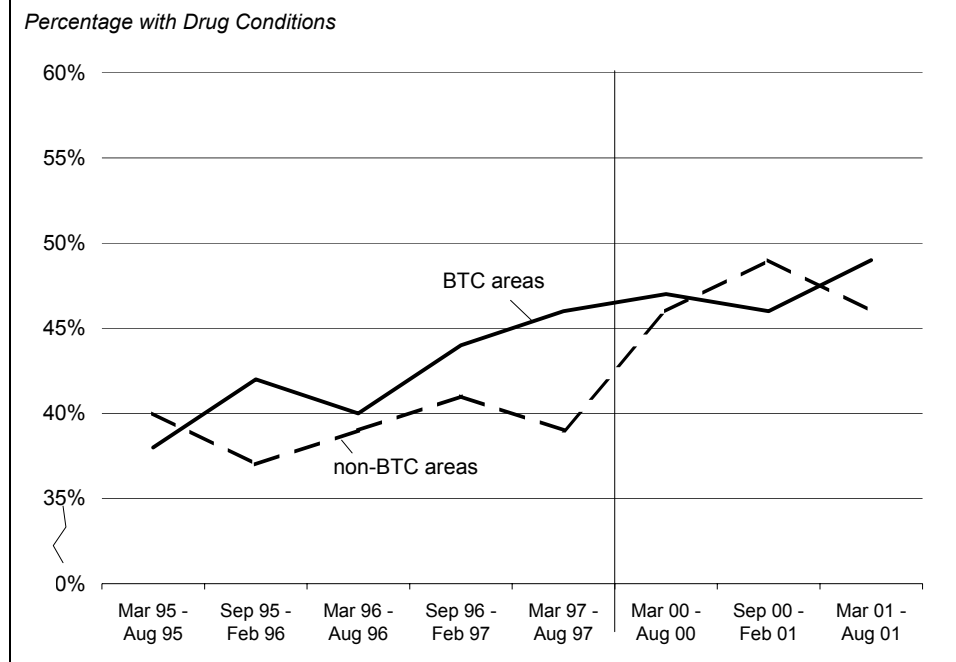
The sample is composed of 5,600 offenders under DPP supervision, selected to represent offenders entering supervision in seven BTC areas and seven non-BTC areas during five time periods before BTC was introduced and three time periods after BTC implementation. Eligible offenders were identified using the intake date and location recorded in the Offender-Based State Correctional Information System II (OBSCIS II), the DPP data system.

All offenders starting supervision during each period were eligible for sample inclusion. This decision reflects the need to consider the apparent changes in the use of drug conditions across the study period. As Figure 1 shows, the likelihood of getting a drug condition increased in both BTC and non-BTC areas during the study period.³

It is not clear what caused the shift in use of drug conditions. BTC and other trends nationally may have increased awareness of the potential benefits or availability of enhanced supervision and treatment. If such awareness led to more widespread use of drug conditions perhaps with less severely addicted offenders, then probationers and parolees after March 2000 might be, as a group, at lower risk of relapse and recidivism. It is also possible that increased awareness could affect sentencing practices by increasing the likelihood that addicted offenders would receive probation with drug conditions, increasing the risk of relapse and recidivism among those with drug conditions. Moreover, the factors influencing assignment of drug conditions could differ between BTC and non-BTC areas.

³ Table A.1 in the Appendix shows the proportion of probationers and parolees with drug conditions by county and time period.

Figure 1. Proportion of Probationers and Parolees With Drug Conditions



To avoid confounding changes in the use of drug conditions with changes due to BTC, the sample selected for the evaluation includes all offenders and is used to compare outcomes for them and the role of drug conditions in combination with BTC rather than focusing only on offenders with drug conditions.

The BTC samples were selected from offenders starting supervision in Baltimore, Charles, Howard, Montgomery, Prince George's, and Washington counties and Baltimore City. To identify the most appropriate counties for comparison from the remaining sixteen counties in Maryland, 2000 census data were analyzed to find the most appropriate matches. Seven non-BTC counties were selected based on county size and distribution of urban/rural populations. The non-BTC areas were Anne Arundel, Carroll, Cecil, Harford, Frederick, St. Mary's, and Wicomico counties.

The sample was selected from multiple pre-and post-BTC time periods to minimize seasonal variations in arrest rates, smooth sharp shifts in arrest rates caused by local enforcement crackdowns or changes in leadership, and allow the analysis to focus on outcomes as fidelity of implementation improved. Defining the post-BTC period was complicated because changes were introduced slowly over a period of time. The Division of Parole and Probation was assigned the responsibility for implementing BTC, but faced serious logistical and resource constraints in meeting the requirements. In the absence of a planning phase, BTC began without written policies and procedures, limited experience with drug testing and no access to certified drug testing laboratories, significant shortages in drug treatment capacity in some areas, lack of

computer hardware and software for monitoring offender compliance, and the need to train large numbers of staff in new procedures and policies. It was not until early 2000 that implementation began in earnest. As a result, pre-BTC recidivism was measured for five time periods between March 1995 through August 1997, and during-BTC recidivism was measured for three time periods from March 2000 through August 2001, skipping the start-up years of 1998 and 1999 and part of 2000 when BTC practices were not widely used. The end date of August 2001 was selected to allow time for the collection and analysis of one year of follow-up data.

For each area and time period, 50 offenders entering supervision were randomly sampled from the potential pool of all offenders entering supervision to represent the distribution of supervision cases across offices within a given jurisdiction.⁴ That is, larger offices contributed more cases to the 50 sampled in each jurisdiction than did smaller offices (within a given 6-month period). Thus, the sample for each time period is proportional to the distribution of offenders entering supervision across offices within the jurisdiction. The sample has 3,500 individuals in the pre-BTC period (50 offenders X 14 jurisdictions X five time periods) and 2,100 individuals in the post-BTC period (50 offenders X 14 jurisdictions X three time periods) for a total of 5,600 cases. Forty-percent of the sample members (n=2,239) had drug conditions attached to their supervision and represent the population targeted by BTC.

Table 1 describes the full BTC and non-BTC samples (columns 1 and 3) and the samples of those with drug conditions (columns 2 and 4). In both BTC and non-BTC areas, the average age of offenders was 30; most were men (80%); and just over a quarter were on probation or parole for a drug offense. However, the offenders in the BTC and non-BTC areas differed significantly in race and alcohol problems. The proportion of white offenders was higher in the more rural, non-BTC counties (69% compared to 48%) as was the proportion with alcohol problems noted in their conditions of supervision (37% compared to 27%).

The significance tests compare the characteristics of the sample with drug conditions to the characteristics of the full sample. The results show that in both BTC and non-BTC areas, offenders with drug conditions were younger (by less than a year) than the full sample of all offenders and more likely have an alcohol condition required as part of supervision.

THE MEASURES

Individual Offender Characteristics

The individual characteristics of offenders available in OBSCIS II were used in the analysis. These included age (measured in years), race (coded as white and other), gender, and the current

⁴ The sample is designed to advance the goal of comparing BTC and non-BTC areas by creating equal numbers of sample members in each county for the quasi-experimental comparisons. For this reason, the sample sizes are not proportional to the size of the population under supervision in each area and results should not be used to estimate the overall effects of BTC on the population of offenders under supervision in these areas.

offense (coded as drug and other). In addition, the records included whether drug, alcohol, or psychiatric conditions were required by the court or Parole Commission, indicating a need for DPP officers to provide services for these problems. The other individual level risk factor included in the analysis was the number of prior arrests, calculated from the criminal history records collected to measure recidivism. The average number of prior arrests was 3.9 for sample members in the BTC areas and 3.6 for those in the non-BTC areas.

Table 1. Comparison of Characteristics of Sample Members

Offender Characteristics	BTC		Non-BTC	
	All Offenders (N=2,800)	Offenders With Drug Conditions (N=1,079)	All Offenders (N=2,800)	Offenders With Drug Conditions (N=1,160)
Mean Age	30.64 years	30.11 years ^a	30.43 years	29.62 years ^a
Race				
White	47.9%	47.6%	68.8%	68.4%
Other race	52.1	52.4	31.2	31.6
Gender				
Male	82.5	83.1	80.1	80.5
Female	17.5	16.9	19.9	19.5
Drug offense	26.4	45.8 ^b	26.0	47.1 ^b
Alcohol condition	26.6	62.5 ^b	36.5	78.0 ^b
Psychiatric condition	5.1	5.4	6.2	5.3

a – T-test significant (alpha<=0.05) This tests the null hypothesis that there is no difference between columns for linear variables

b – Asymmetric Uncertainty Coefficient significant (alpha<=0.05) This tests the null hypothesis that there is no difference in percentages between columns for categorical variables

County Variation

The counties given additional funds for BTC differed from non-BTC jurisdictions in demographic characteristics, size, and urban problems. To be able to isolate the independent effects of BTC, the analysis includes the following measures to control for differences in population risk indicators, pre-existing rates of recidivism, and rates of reported crime and arrests.

County demographics. Measures of county differences in recidivism risk came from the 2000 U.S. Census.⁵ These include the percentage of the residents that are white, the percent of males in the workforce, the percent of housing units that are owner occupied, the percent of households that are female-headed, the percent of households receiving public assistance, the percent of families living below the poverty line, and the high school dropout rate (Table 2). These variables are associated with differences in crime rates and access to health care and are used to control for county-level differences in the problems faced by probationers and parolees in their community.

⁵ U.S. Census Bureau 22nd Census of Population and Housing, 2000

Table 2. Demographic Characteristics Of The Sample Areas

Supervising Jurisdiction	Percent White	Percent Males in Work Force	Percent Owner Occupied Housing Units	Percent Female-Headed Households	Percent Households Receiving Public Assistance	Percent Below the Poverty Line	High School Dropout Rate
BTC Areas							
Baltimore City	32.6%	32.3%	50.3%	25.0%	7.3%	22.9%	31.6%
Baltimore County	75.5	39.3	67.6	12.8	1.7	6.5	15.7
Charles County	70.2	40.9	78.2	14.5	1.8	5.5	14.2
Howard County	76.0	44.6	73.8	9.5	1.0	3.9	6.9
Montgomery County	67.3	40.9	68.7	10.5	1.3	5.4	9.7
Prince George's County	28.5	40.2	61.8	19.6	2.0	7.7	15.1
Washington County	90.7	37.3	65.6	10.7	2.3	9.5	22.2
Non-BTC Areas							
Anne Arundel County	82.6	40.7	75.5	11.1	1.2	5.1	13.6
Carroll County	96.4	43.6	82.0	8.3	1.2	3.8	14.7
Cecil County	94.5	42.6	75.0	11.1	2.1	7.2	18.8
Frederick County	90.6	44.4	75.9	9.4	1.4	4.5	12.9
Harford County	88.0	42.5	78.0	10.2	1.5	4.9	13.3
St Mary's County	83.0	41.7	71.8	10.6	2.2	7.2	14.7
Wicomico County	73.6	42.0	66.5	14.1	2.9	12.8	19.3

Pre-existing county differences in recidivism. Recidivism rates, measuring rearrest in the year after starting probation and parole, were created from the criminal history records of samples from the time periods before the introduction of BTC (March 1995 through August 1997). Prior rates of recidivism during the first year of supervision were included in the statistical models to control for pre-existing differences between the counties in arrests of probationers and parolees, due both to local enforcement practices and local crime rates among offenders. The analysis can then estimate the relative change in recidivism in counties following the introduction of BTC.

County changes in crime and enforcement. To further control for these differences, per capita arrest rates were calculated for each county in the sample from the Uniform Crime Report data for the pre- and post-BTC time periods (see Table 3). The per-capita arrest rates were included in the statistical models to help control for police crackdowns, targeted enforcement initiatives, and other enforcement changes across time and areas that could independently affect the likelihood of arrest of a sample member.

Table 3. County Arrest Rates Per 1000 Population Before and During BTC

Supervising Jurisdiction	Pre BTC ^a	During BTC ^b
BTC Areas		
Baltimore City	10.9 per 1,000 pop.	13.3 per 1,000 pop.
Baltimore County	5.3	5.2
Charles County	6.1	7.1
Howard County	4.4	4.3
Montgomery County	2.5	2.4
Prince George's County	5.3	5.4
Washington County	4.9	5.5
Non BTC Areas		
Anne Arundel County	5.9	5.7
Carroll County	2.7	2.9
Cecil County	7.7	8.2
Frederick County	4.6	4.4
Harford County	3.4	4.0
St. Mary's County	5.6	6.2
Wicomico County	7.5	7.8

a -- Average annual figures for 1995-1997

b -- Annual figure for 2000

Source: Consortium for Political and Social Research. 2003. "National Archive of Criminal Justice Data."

BTC Implementation Measures

The process evaluation of BTC (Taxman, Reedy, Moline, Ormand, and Yancey, 2003) indicates that BTC implementation started slowly and improved over time. To account for this gradual implementation, this analysis examines outcomes during the period of September 2000 through August 2001. By this time, written policies on BTC implementation had been issued and training for the required changes in supervision practices had also begun. The four-year process study of BTC (1999-2002) found improvements in the level of program implementation over this period, particularly in the last two years (Taxman, et al., 2003).

Indicators of BTC implementation were constructed from data provided by (HATS). Although HATS contains data on individuals, aggregate measures of implementation were used instead of individual records of drug test results, compliance, and sanctions. Obtaining informed consent from each sample member to use their HATS data for research purposes would have required locating sample members years after the start of a period of probation or parole, a task judged to be extraordinarily expensive and likely to fail.

HATS data from two source files were used: drug test results and sanctions. The measures used in this analysis included the number of drug tests per person under supervision in each BTC

county, the number of sanctions per person under supervision in the county, and the ratio of sanctions to positive drug tests⁶ during the three BTC six-month time periods (March, 2000 through August, 2001). The ratio of sanctions to drug tests is used to measure the extent to which infractions of drug conditions resulted in a penalty for continued drug use. Unfortunately, a major form of drug test failure, namely failure-to-appear at a scheduled drug test, was not included in the indicator due to problems in data reliability. In addition, the measure also fails to include tampered drug tests, which are encountered daily and are treated as a BTC infraction. This may have reduced the ability of the indicator to measure the underlying concept – the enforcement of BTC conditions. The average values for each variable are shown by county and time period in Table 4.

Recidivism

Recidivism is measured by an arrest for a new offense in the first year of supervision using data from the Criminal History Records Information (CHRI) maintained by the Department of Public Safety and Correctional Services' (DPSCS) Criminal Justice Information System (CJIS).⁷ Arrest warrants issued for violation of probation or parole conditions were not counted as new offenses. These warrants were used to discourage offender non-compliance with supervision requirements under BTC and therefore it was inappropriate to consider them to be new offenses.

The analysis examines four recidivism measures, including 1) any arrest, 2) the number of arrests, 3) any drug arrest, and 4) the number of drug arrests. The number of prior arrests, used as a control variable in the analysis, also came from the criminal history check.

For each sample member, the data include the type and date of arrests before the time of sample selection and during the following year. Based on a unique identification number assigned to each offender (the SID) and included in both systems, criminal history records were found for 4,713 sample members (84% of the full sample). Missing data resulted from no SID number in OBSCIS II for 623 individuals, and no criminal record in CHRI for 264 individuals with an SID.⁸ Table 5 compares cases with and without available criminal history records to assess the effects of missing data on the representativeness of the sample available for analysis.

Criminal history records were more likely to be missing for older offenders in the non-BTC areas. Other differences between sample members with and without criminal history within BTC and non-BTC areas were not statistically significant, although some appear large. The statistical models control for the variables found to be significantly related to missing criminal history records (gender, current offense, and special conditions of supervision).

⁶ The numbers under supervision in each time period by area were provided by DPP staff.

⁷ CJIS is the main repository for Maryland criminal justice data, and collects automated history data (local and national) collected at arrest, incarceration history from the Offender Based State Correctional Information System (OBSCIS I) and probation and parole histories from OBSCIS II. These data include detailed information on key criminal justice history indicators, including prior arrests, dispositions and time served, including charge, and post-release supervision.

⁸ There are several possible reasons for missing criminal history records, including data processing errors or participation in diversionary programs, which results in expunging the records.

Table 4. Indicators of BTC Implementation

Supervising Jurisdiction	Mar 00 – Aug 00	Sep 00 – Feb 01	Mar 01 – Aug 01
Baltimore City			
Average Number of Sanctions	0.11	0.09	0.17
Average Number of Drug Tests	6.70	5.09	4.62
Ratio of Sanctions to Positive Drug Tests	0.17	0.15	0.22
Baltimore County			
Average Number of Sanctions	0.20	0.28	0.33
Average Number of Drug Tests	5.52	4.34	4.02
Ratio of Sanctions to Positive Drug Tests	0.40	0.62	0.63
Charles County			
Average Number of Sanctions	0.36	0.27	0.24
Average Number of Drug Tests	14.24	8.63	7.18
Ratio of Sanctions to Positive Drug Tests	0.32	0.30	0.25
Howard County			
Average Number of Sanctions	0.11	0.17	0.28
Average Number of Drug Tests	7.48	6.69	5.00
Ratio of Sanctions to Positive Drug Tests	0.18	0.26	0.45
Montgomery County			
Average Number of Sanctions	0.15	0.31	0.44
Average Number of Drug Tests	9.06	5.91	5.39
Ratio of Sanctions to Positive Drug Tests	0.17	0.53	0.55
Prince George's County			
Average Number of Sanctions	0.39	0.33	0.45
Average Number of Drug Tests	6.94	5.10	4.82
Ratio of Sanctions to Positive Drug Tests	0.58	0.54	0.59
Washington County			
Average Number of Sanctions	0.72	0.84	0.83
Average Number of Drug Tests	16.80	12.33	10.35
Ratio of Sanctions to Positive Drug Tests	0.45	0.67	0.58

THE ANALYSIS PLAN

The study tested the effects of BTC on crime among probationers and parolees by examining the following questions, first for all probationers and parolees, and then for probationers and parolees with drug conditions:

- Were probationers and parolees in BTC areas less likely than similar offenders in non-BTC areas to be arrested on a new offense in their first year of supervision?
- Were probationers and parolees in areas with indicators of higher levels of BTC implementation less likely than similar offenders in other areas to be arrested on a new offense in their first year of supervision?

To answer these questions, the analyses tested the null hypothesis that there was no difference in the arrests of probationers and parolees related to supervision in a BTC area or to the use of drug tests and sanctions in BTC areas (one-tail statistical tests). The recidivism measures included arrest for any offense, number of arrests, arrest for a drug offense, and number of arrests for drug offenses. The general model is shown below:

$$\text{Arrest} = f(\text{client risk, county risk, BTC area (yes/no), time period (pre/post), implementation})$$

Models were estimated using logistic regression for the likelihood of arrest and Poisson regression for numbers of arrest. Generalized Equation Estimation (GEE) was used to control for variation at both the county and individual levels and accommodate dependence among observations within a jurisdiction (Liang and Zeger, 1986). The control variables⁹ used in all models include:

- **Individual characteristics of sample members:** age in years, age-squared to account for the non-linear form of the relationship between crime and age, race (white and other), gender, a gender-race-age interaction used to control for the generally higher arrest rates of young black males, offense for which they were placed on probation or parole (drug and other), number of prior arrests, and supervision conditions set by the judge or Parole Commission. These included services for the following problems: alcohol (yes/no), drug (yes/no), psychological (yes/no), and other (yes/no).
- **County characteristics:** percent white, percent males in labor force, percent of housing units occupied by owners, percent of households headed by women, percent of households receiving public assistance, percent of households below the poverty line, and arrest rate per 1000 population pre-and post-BTC.

⁹ Models were estimated using SAS, PROC GENMOD (SAS Institute Inc. 1997). All models used 4,712 observations (one person dropped due to missing age) and had 4,689 degrees of freedom.

The models also contain variables to indicate if the sample members were under supervision in a BTC or non-BTC county and whether their first year of supervision (the period for which recidivism is measured) occurred before or after BTC implementation.

Interaction terms are included to specify which sample members might have received BTC: 1) were under supervision in a BTC jurisdiction after BTC was implemented (yes/no, or 2) had drug conditions required and were under supervision in a BTC jurisdiction after BTC was implemented (yes/no). In the tests of the effects of the level of BTC implementation, the interactions were between these dichotomous variables and linear variables measuring: 1) the number of drug tests per supervisee in the specific BTC county, 2) the number of sanctions per supervisee in the specific BTC county, and 3) the number of sanctions per positive drug tests in the specific BTC county.¹⁰

Table 5. Comparison of Characteristics of Sample Members With and Without Missing Criminal History Data

Individual Characteristics	BTC		Non BTC	
	With Arrest Data (N=2,325)	Without Arrest Data (N=475)	With Arrest Data (N=2,388)	Without Arrest Data (N=412)
Mean Age	30.5 years	31.35 years	30.21 years	31.72 years ^a
Race				
White	48.2%	46.1%	66.7%	80.6% ^b
Other race	51.8	53.9	33.3	19.4
Gender				
Male	85.0	70.3 ^b	81.7	71.1 ^b
Female	15.0	29.7	18.3	28.9
Drug offense	28.4	16.6 ^b	27.5	17.2 ^b
Alcohol condition	29.1	14.5 ^b	38.1	27.2 ^b
Drug condition	42.3	20.2 ^b	44.1	26.0 ^b
Psychiatric condition	5.1	5.3	5.9	8.3
Other condition	54.2	59.2	56.6	66.7 ^b

a – T-test Significant (alpha=0.05) T-test significant (alpha<=0.05) This tests the null hypothesis that there is no difference between columns for linear variables

b – Asymmetric Uncertainty Coefficient significant (alpha<=0.05) This tests the null hypothesis that there is no difference in percentages between columns for categorical variables

¹⁰ In the preliminary findings released in February of 2003, outcomes for individual BTC counties were presented and showed lower recidivism rates in Howard County than in other areas. However, for the final report, the analysis focused directly on the measures of BTC implementation since many factors within counties other than BTC could affect the likelihood of arrest.

Table 6. Average Number of Arrests per Offender in the First Year of Supervision by County and Time

Supervising Jurisdiction	Mar 95 – Aug 95	Sep 95 – Feb 96	Mar 96 – Aug 96	Sep 96 – Feb 97	Mar 97 – Aug 97	Mar 00 – Aug 00	Sep 00 – Feb 01	Mar 01 – Aug 01
BTC Areas								
Baltimore City	0.30	0.29	0.37	0.43	0.38	0.36	0.31	0.38
Baltimore County	0.24	0.26	0.42	0.35	0.41	0.15	0.35	0.44
Charles County	0.40	0.30	0.29	0.30	0.28	0.16	0.25	0.26
Howard County	0.29	0.15	0.28	0.34	0.28	0.29	0.26	0.18
Montgomery County	0.44	0.28	0.32	0.33	0.23	0.41	0.24	0.50
Prince George’s County	0.27	0.13	0.13	0.15	0.18	0.27	0.21	0.44
Washington County	0.21	0.33	0.33	0.20	0.21	0.31	0.18	0.20
Non BTC Areas								
Anne Arundel County	0.43	0.37	0.23	0.41	0.27	0.40	0.20	0.49
Carroll County	0.43	0.24	0.35	0.24	0.22	0.34	0.29	0.27
Cecil County	0.33	0.08	0.21	0.20	0.27	0.28	0.32	0.11
Frederick County	0.38	0.25	0.31	0.23	0.30	0.19	0.26	0.28
Harford County	0.23	0.20	0.23	0.32	0.24	0.10	0.16	0.27
St. Mary’s County	0.23	0.26	0.26	0.30	0.26	0.26	0.25	0.31
Wicomico County	0.25	0.38	0.33	0.18	0.32	0.20	0.40	0.21

In the tables below, the tests of the effects of BTC are shown the rows with a double border. If the impact of BTC was statistically significant, the probability level is indicated by the letter next to the estimate (* refers to $p \leq .001$, ** refers to $p \leq .01$, and *** refers to $p \leq .10$).

RESULTS

Question 1A. Was recidivism among all offenders under supervision lower in BTC areas than in non-BTC areas?

Overall, the likelihood of arrest among all probationers remained relatively stable within a range except for a sharp rise in arrests in BTC areas in the last period (March – August 2001) as shown in Figure 2. The arrest rates for BTC and non-BTC counties before and after implementation in Table 3 show that the largest increase in arrest rates after BTC implementation occurred in Baltimore City. However, the likelihood of an arrest for a drug offense rose steadily in both BTC and non-BTC areas and was higher in BTC areas. The numbers of arrests and, specifically drug arrests, rose during the study period as shown in Figure 3. BTC efforts to reduce criminal activity by addressing drug use among offenders must thus be interpreted in light of these trends.

The regression results shown in Table 7 control for individual and county characteristics that can influence the likelihood and number of arrests and the general rise in arrests of probationers and parolees. The results show no significant difference in the likelihood or number of arrests among all probationers and parolees under supervision in BTC and non-BTC areas after the implementation of BTC.

Question 1B. Was recidivism among offenders with drug conditions required as part of their supervision lower in BTC areas than in non-BTC areas?

Among probationers and parolees with a drug condition, the overall likelihood of arrest fell slightly during the study period, while the likelihood of a drug arrest rose in both BTC and non-BTC areas (Figure 4). The numbers of arrests and drug arrests (shown in Figure 5) followed generally the same pattern.

The regressions used to estimate the impact of BTC for offenders with drug conditions control for the individual and county differences that may influence these trends. The results, shown in Table 8, indicate that the likelihood and number of arrests for drug offenses (but not all offenses) were significantly lower in BTC areas than in non-BTC areas after the implementation of BTC among probationers and parolees with drug conditions. These were the probationers and parolees targeted for BTC intervention. However, the significance only attained the probability level of 0.1.

Figure 2. Percentage of All Probationers and Parolees Arrested in First Year of Supervision

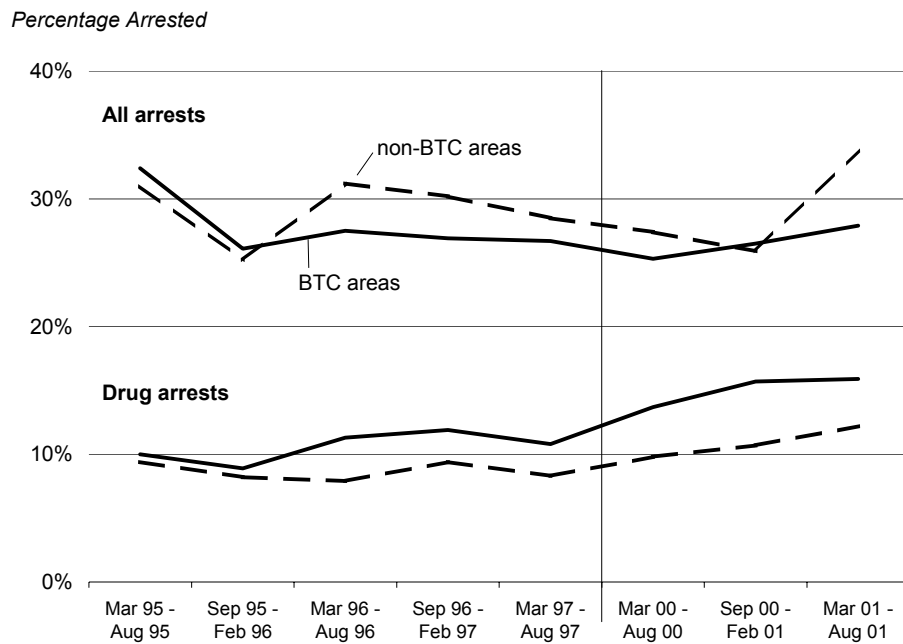


Figure 3. Average Number of Arrests of All Probationers and Parolees in First Year of Supervision

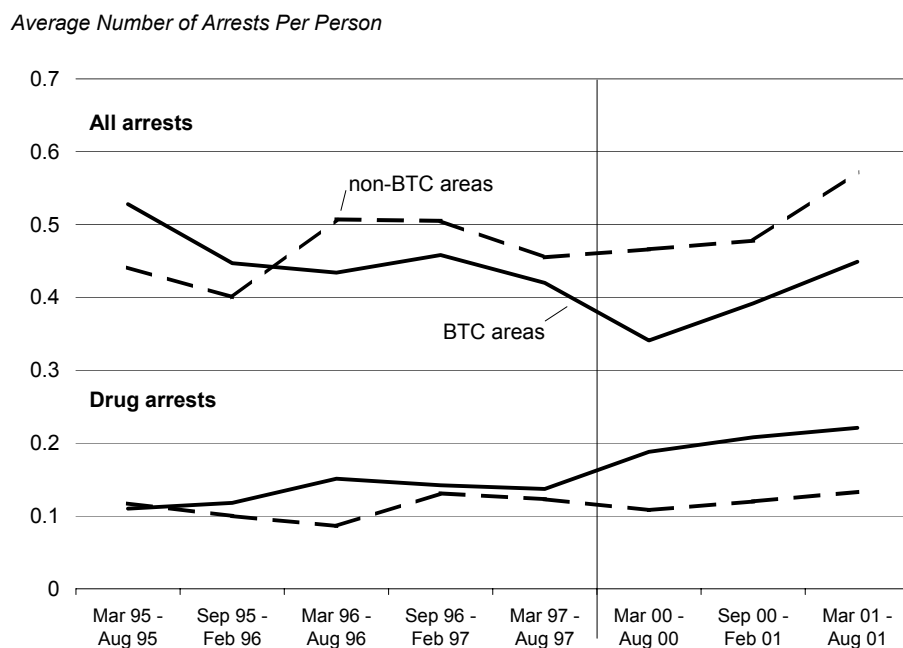


Table 7. Regression Models Testing the Impact of BTC on All Offenders: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	0.937	3.650	2.375	3.084
BTC Impact				
Jurisdiction (BTC=1)	-0.070	-0.110	-0.115	-0.152
Time Period (POST=1)	-0.011	0.303*	-0.099***	0.111
BTC X POST (=1)	0.005	0.069	0.153	0.261
Individual Characteristics				
Age in years	-0.053**	-0.007	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285*	-0.309**	-0.132***	-0.250***
Gender (Male = 1)	0.162	0.178	0.072	-0.019
Young Black Male (yes/no)	0.186	0.018	0.208**	0.102
Current Offense (Drug = 1)	-0.292*	0.346*	-0.271*	0.291*
Alcohol Condition (yes=1)	0.137	0.015	0.090	-0.096
Drug Condition (yes=1)	0.011	0.173	0.032	0.224
Psychological Condition (yes=1)	-0.202***	-0.693**	-0.131	-0.745*
Other Condition (yes=1)	-0.178*	-0.196*	-0.117**	-0.156**
Number of prior arrests	0.085*	0.056*	0.070*	0.056*
County Characteristics				
Arrests per capita	-0.080	0.011	-0.027	0.013
% white	0.028	-0.003	0.003	0.000
% males in work force	-0.082**	-0.123	-0.079*	-0.113
% owner occupied housing units	0.003	0.007	0.015	0.004
% female headed households	0.123	-0.028	-0.008	-0.021
% households rec. public assistance	0.008	0.239	0.001	0.323
% below poverty line	0.067***	-0.038	0.078***	-0.043
HS dropout rate	-0.084	-0.050	-0.060	-0.059
Select Model Diagnostics				
# obs. included in regression	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,388	3,091	5,636	2,758

Significance: * = p < 0.01; ** = p<0.05; *** = p<0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Question 2A. Was recidivism among all offenders under supervision lower in areas with higher levels of BTC implementation than in other areas?

The results of the regressions used to estimate the impact of BTC for all offenders are shown in Tables 9 to 11. The results show only one significant difference in the likelihood or number of arrests among all probationers and parolees under supervision associated with the level of implementation of BTC. The likelihood of arrest for a drug offense was significantly lower ($p < .1$) for probationers and parolees in BTC areas in which more drug tests per offender under supervision were administered than for probationers and parolees in other areas (non-BTC areas and BTC areas that administered fewer drug tests per offender).

Question 2B. Was recidivism among offenders with drug conditions required as part of their supervision lower in areas with higher levels of BTC implementation than in other areas?

The results of the regressions used to estimate the impact of BTC for offenders with drug conditions are shown in Tables 12 to 14. The results show significant differences in the likelihood or number of arrests among probationers and parolees with a drug condition associated with two of the three indicators of level of BTC implementation. The likelihood of arrest for a drug offense was significantly lower ($p < .1$) for probationers and parolees in BTC areas than for probationers and parolees in other areas¹¹ when more drug tests per offender under supervision were administered. Similar reductions in arrests were found among probationers and parolees in BTC areas that delivered a higher number of sanctions per person under supervision for three of the four recidivism measures: the likelihood of any arrest, the number of arrests and the number of drug arrests. However, the second BTC implementation measure based on sanctions data, the number of sanctions per positive drug test, was not a significant predictor of reductions in arrests among probationers and parolees with drug conditions in BTC areas.

¹¹ Other areas include non-BTC areas and BTC areas that used BTC strategies less intensively.

Figure 4. Percentage of Probationers and Parolees with a Drug Condition Arrested in The First Year of Supervision

Percentage Re-Arrested

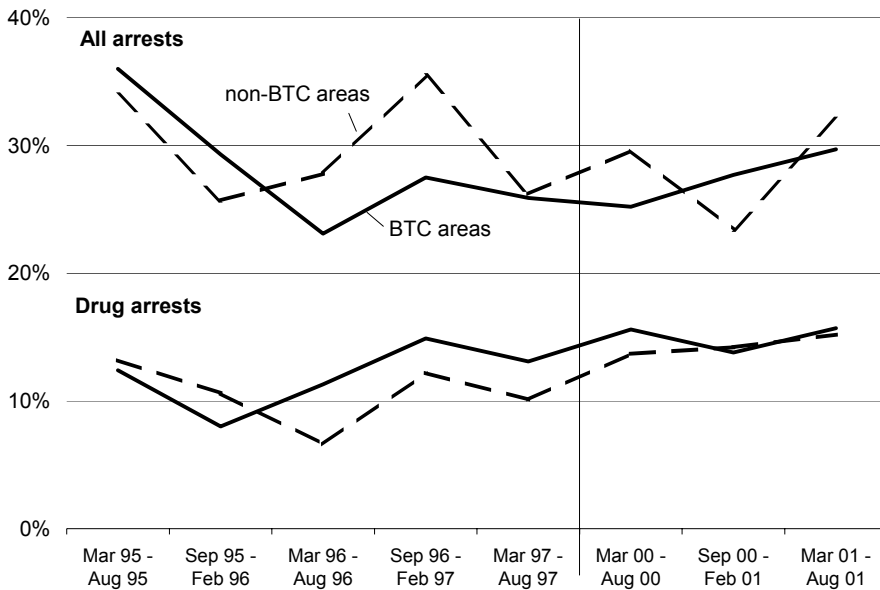


Figure 5. Average Number of Subsequent Arrests of Probationers and Parolees with a Drug Condition in First Year of Supervision

Average Number Of Arrests Person

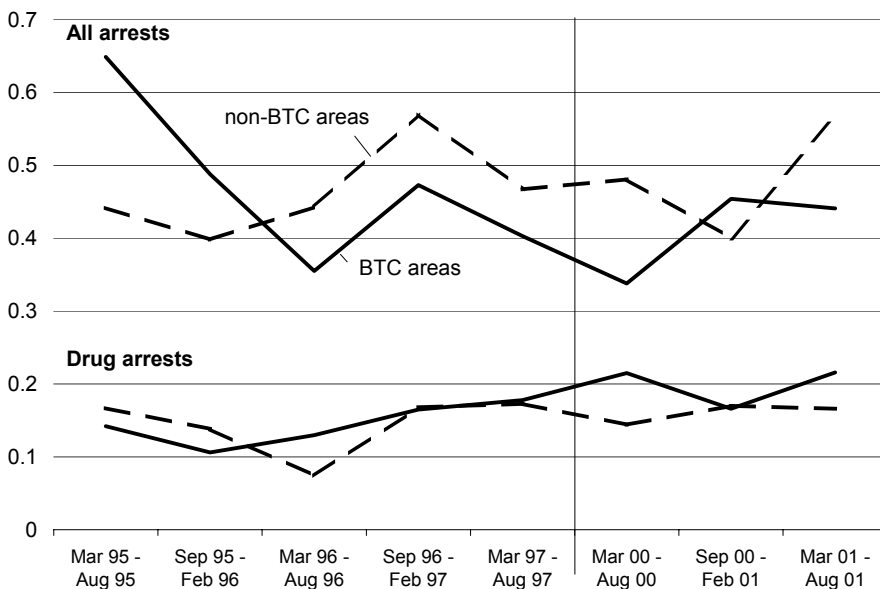


Table 8. Regression Models Testing the Impact of BTC on Offenders with Drug Conditions: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	0.985	3.951	2.569	3.817
BTC Impact				
Jurisdiction (BTC=1)	-0.048	-0.009	-0.045	0.043
Time Period (POST=1)	0.012	0.394*	-0.014	0.291*
BTC X POST X DRUGCON	-0.101	-0.239***	-0.046	-0.184***
Individual Characteristics				
Age in years	-0.054**	-0.008	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285**	-0.308**	-0.132***	-0.249***
Gender (Male = 1)	0.162	0.179	0.074	-0.018
Young Black Male (yes/no)	0.184	0.015	0.207**	0.101
Current Offense (Drug = 1)	-0.293*	0.345*	-0.270*	0.292*
Alcohol Condition (yes=1)	0.140	0.026	0.096	-0.083
Drug Condition (yes=1)	0.028	0.224	0.038	0.265
Psychological Condition (yes=1)	-0.199***	-0.684**	-0.126	-0.729*
Other Condition (yes=1)	-0.177*	-0.192**	-0.116**	-0.151**
Number of prior arrests	0.085*	0.057*	0.071*	0.057*
County Characteristics				
Arrests per capita	-0.076	0.028	-0.015	0.051
% white	0.027	-0.008	0.000	-0.011
% males in work force	-0.082**	-0.125	-0.080*	-0.117
% owner occupied housing units	0.004	0.011	0.017	0.011
% female headed households	0.116	-0.057	-0.026	-0.087
% households rec. public assistance	0.007	0.245	0.001	0.339
% below poverty line	0.068***	-0.041	0.076***	-0.054
HS dropout rate	-0.083	-0.043	-0.055	-0.041
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,387	3,089	5,639	2,760

Significance: * = p < 0.01; ** = p < 0.05; *** = p < 0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Table 9. Regression Models Testing the Impact of BTC Drug Tests per Supervisee on All Offenders: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	1.059	3.962	2.571	3.738
BTC Impact				
Jurisdiction (BTC=1)	-0.005	0.021	-0.032	0.018
Time Period (POST=1)	0.048	0.415*	-0.003	0.270*
Drug Test Per Supervisee X Drug Condition	-0.017	-0.022	-0.006	-0.007
Individual Characteristics				
Age in years	-0.054**	-0.007	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.284**	-0.307**	-0.132***	-0.249***
Gender (Male = 1)	0.164	0.181	0.074	-0.018
Young Black Male (yes/no)	0.184	0.017	0.207**	0.103
Current Offense (Drug = 1)	-0.293*	0.347*	-0.269*	0.295*
Alcohol Condition (yes=1)	0.139	0.020	0.095	-0.090
Drug Condition (yes=1)	0.009	0.169	0.029	0.219
Psychological Condition (yes=1)	-0.199***	-0.690**	-0.126	-0.735*
Other Condition (yes=1)	-0.177*	-0.195*	-0.116**	-0.154**
Number of prior arrests	0.086*	0.057*	0.071*	0.057*
County Characteristics				
Arrests per capita	-0.068	0.033	-0.014	0.047
% white	0.024	-0.010	-0.001	-0.009
% males in work force	-0.084**	-0.129	-0.081*	-0.118
% owner occupied housing units	0.007	0.015	0.018	0.011
% female headed households	0.100	-0.068	-0.029	-0.078
% households rec. public assistance	-0.009	0.213	-0.005	0.321
% below poverty line	0.071***	-0.034	0.078***	-0.050
HS dropout rate	-0.077	-0.037	-0.053	-0.042
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,386	3,089	5,639	2,760

Significance: * = p < 0.01; ** = p < 0.05; *** = p < 0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Table 10. Regression Models Testing the Impact of BTC Sanctions per Supervisee on All Offenders: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	0.984	4.015	2.566	3.751
BTC Impact				
Jurisdiction (BTC=1)	-0.056	0.002	-0.052	0.015
Time Period (POST=1)	0.005	0.413*	-0.019	0.272*
Sanction Per Supervisee	-0.084	-0.455***	-0.024	-0.158
Individual Characteristics				
Age in years	-0.053**	-0.008	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285*	-0.307**	-0.132***	-0.249***
Gender (Male = 1)	0.162	0.180	0.074	-0.018
Young Black Male (yes/no)	0.185	0.017	0.207**	0.103
Current Offense (Drug = 1)	-0.292*	0.346*	-0.269*	0.295*
Alcohol Condition (yes=1)	0.137	0.016	0.094	-0.091
Drug Condition (yes=1)	0.011	0.173	0.030	0.220
Psychological Condition (yes=1)	-0.201***	-0.689**	-0.127	-0.734*
Other Condition (yes=1)	-0.179*	-0.197*	-0.116**	-0.155**
Number of prior arrests	0.085*	0.057*	0.071*	0.057*
County Characteristics				
Arrests Per Capita	-0.079	0.020	-0.017	0.041
% white	0.028	-0.007	0.000	-0.009
% males in work force	-0.082**	-0.127	-0.080*	-0.118
% owner occupied housing units	0.003	0.010	0.017	0.009
% female headed households	0.119	-0.054	-0.024	-0.074
% households rec. public assistance	0.002	0.198	-0.001	0.314
% below poverty line	0.068***	-0.035	0.077***	-0.049
HS dropout rate	-0.082	-0.036	-0.055	-0.042
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,387	3,089	5,639	2,760

Significance: * = p < 0.01; ** = p < 0.05; *** = p < 0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Table 11. Regression Models Testing the Impact of BTC Sanctions per Positive Drug Test on All Offenders: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	0.915	3.775	2.479	3.520
BTC Impact				
Jurisdiction (BTC=1)	-0.082	-0.077	-0.094	-0.092
Time Period (POST=1)	-0.030	0.337*	-0.087	0.149*
Sanctions Per Positive Drug Test	0.103	0.005	0.299	0.434
Individual Characteristics				
Age in years	-0.053**	-0.007	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285*	-0.309**	-0.132***	-0.250***
Gender (Male = 1)	0.162	0.179	0.072	-0.019
Young Black Male (yes/no)	0.186	0.018	0.206**	0.103
Current Offense (Drug = 1)	-0.292*	0.347*	-0.268*	0.296*
Alcohol Condition (yes=1)	0.136	0.016	0.093	-0.092
Drug Condition (yes=1)	0.011	0.172	0.029	0.219
Psychological Condition (yes=1)	-0.202***	-0.692**	-0.132	-0.743*
Other Condition (yes=1)	-0.178*	-0.196*	-0.115**	-0.153**
Number of prior arrests	0.085*	0.056*	0.070*	0.056*
County Characteristics				
Arrests per capita	-0.079	0.017	-0.012	0.050
% white	0.028	-0.005	-0.001	-0.009
% males in work force	-0.082	-0.124	-0.080	-0.116
% owner occupied housing units	0.004	0.008	0.019	0.012
% female headed households	0.121	-0.037	-0.028	-0.073
% households rec. public assistance	0.013	0.240	0.016	0.352
% below poverty line	0.068	-0.040	0.077	-0.048
HS dropout rate	-0.085	-0.048	-0.057	-0.050
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,388	4,712	5,637	2,760

Significance: * = $p < 0.01$; ** = $p < 0.05$; *** = $p < 0.1$

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Table 12. Regression Models Testing the Impact of BTC Drug Tests per Supervisee on Offenders with a Drug Condition: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	0.981	3.899	2.541	3.724
BTC Impact				
Jurisdiction (BTC=1)	-0.036	0.005	-0.029	0.064
Time Period (POST=1)	0.016	0.395*	-0.003	0.299*
Drug Test Per Supervisee X Drug Condition	-0.017**	-0.034**	-0.013***	-0.030**
Individual Characteristics				
Age in years	-0.054**	-0.008	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285**	-0.307**	-0.132***	-0.248***
Gender (Male = 1)	0.163	0.182	0.075	-0.015
Young Black Male (yes/no)	0.183	0.013	0.206**	0.100
Current Offense (Drug = 1)	-0.294*	0.343*	-0.271*	0.292*
Alcohol Condition (yes=1)	0.142	0.028	0.099	-0.080
Drug Condition (yes=1)	0.031	0.223	0.046	0.269
Psychological Condition (yes=1)	-0.199***	-0.686**	-0.124	-0.730*
Other Condition (yes=1)	-0.177*	-0.192**	-0.115**	-0.150**
Number of prior arrests	0.085*	0.057*	0.071*	0.057*
County Characteristics				
Arrests per capita	-0.074	0.030	-0.013	0.052
% white	0.026	-0.009	-0.001	-0.012
% males in work force	-0.083**	-0.127	-0.080*	-0.118
% owner occupied housing units	0.005	0.014	0.019	0.015
% female headed households	0.110	-0.064	-0.031	-0.095
% households rec. public assistance	-0.001	0.222	-0.006	0.321
% below poverty line	0.070***	-0.034	0.079***	-0.048
HS dropout rate	-0.080	-0.039	-0.053	-0.037
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,386	3,088	5,637	2,757

Significance: * = p < 0.01; ** = p<0.05; *** = p<0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Table 13. Regression Models Testing the Impact of BTC Sanctions per Supervisee on Offenders with a Drug Condition: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	1.001	3.913	2.560	3.725
BTC Impact				
Jurisdiction (BTC=1)	-0.045	-0.020	-0.041	0.033
Time Period (POST=1)	0.012	0.385*	-0.010	0.283*
Sanction Per Supervisee X Drug Condition	-0.298***	-0.594***	-0.177	-0.461***
Individual Characteristics				
Age in years	-0.054**	-0.009	-0.030	0.012
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285**	-0.309**	-0.132***	-0.249***
Gender (Male = 1)	0.163	0.181	0.075	-0.016
Young Black Male (yes/no)	0.183	0.011	0.206**	0.099
Current Offense (Drug = 1)	-0.294*	0.343*	-0.271*	0.292*
Alcohol Condition (yes=1)	0.141	0.024	0.097	-0.085
Drug Condition (yes=1)	0.028	0.212	0.039	0.251
Psychological Condition (yes=1)	-0.200***	-0.688**	-0.126	-0.732*
Other Condition (yes=1)	-0.179*	-0.196*	-0.117**	-0.155**
Number of prior arrests	0.085*	0.057*	0.071*	0.057*
County Characteristics				
Arrests per capita	-0.078	0.019	-0.017	0.040
% white	0.027	-0.007	0.000	-0.009
% males in work force	-0.082**	-0.126	-0.080*	-0.118
% owner occupied housing units	0.004	0.010	0.017	0.010
% female headed households	0.115	-0.051	-0.026	-0.078
% households rec. public assistance	-0.004	0.214	-0.006	0.313
% below poverty line	0.069***	-0.035	0.078***	-0.048
HS dropout rate	-0.080	-0.040	-0.053	-0.040
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,386	3,089	5,638	2,759

Significance: * = p < 0.01; ** = p < 0.05; *** = p < 0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

Table 14. Regression Models Testing the Impact of BTC Sanctions per Positive Drug Test on Offenders with a Drug Condition: Likelihood and Number of Arrests in First Year of Supervision

	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
Intercept	0.959	3.834	2.559	3.701
BTC Impact				
Jurisdiction (BTC=1)	-0.054	-0.027	-0.052	0.015
Time Period (POST=1)	0.009	0.389*	-0.020	0.275*
Sanctions Per Positive Drug Test X Drug Condition	-0.206	-0.507	-0.039	-0.277
Individual Characteristics				
Age in years	-0.054**	-0.008	-0.029	0.013
Age X Age	0.000	0.000	0.000	-0.001
Race (White = 1)	-0.285**	-0.308**	-0.132***	-0.249***
Gender (Male = 1)	0.163	0.181	0.074	-0.017
Young Black Male (yes/no)	0.184	0.013	0.207**	0.101
Current Offense (Drug = 1)	-0.294*	0.343*	-0.270*	0.293*
Alcohol Condition (yes=1)	0.139	0.023	0.095	-0.087
Drug Condition (yes=1)	0.025	0.215	0.032	0.244
Psychological Condition (yes=1)	-0.200***	-0.685**	-0.127	-0.731*
Other Condition (yes=1)	-0.178*	-0.195*	-0.116**	-0.154**
Number of prior arrests	0.085*	0.057*	0.071*	0.057*
County Characteristics				
Arrests per capita	-0.080	0.014	-0.017	0.039
% white	0.028	-0.004	0.000	-0.007
% males in work force	-0.082**	-0.124	-0.080*	-0.117
% owner occupied housing units	0.002	0.007	0.017	0.008
% female headed households	0.121	-0.037	-0.023	-0.067
% households rec. public assistance	0.003	0.230	0.000	0.326
% below poverty line	0.068***	-0.039	0.076***	-0.052
HS dropout rate	-0.083	-0.046	-0.055	-0.045
Select Model Diagnostics				
Number of observations	4,712	4,712	4,712	4,712
Average of Dependent Variable	0.28	0.11	0.46	0.14
Deviance (d.f./value)	5,387	3,090	5,639	2,760

Significance: * = p < 0.01; ** = p < 0.05; *** = p < 0.1

Test of BTC impact is one-tailed; all other significant tests are two-tailed.

SUMMARY OF FINDINGS

In all analyses, the null hypothesis that there was no difference in the arrests for probationers and parolees in BTC and non-BTC areas following BTC implementation was tested by the inclusion of the interaction terms shown in Tables 7 through 14. The findings are summarized in Table 15. The first column describes specific hypotheses about the effects of BTC tested in these models shown above. The significance of BTC effects on each arrest measure is shown in the next four columns.

Table 15. Tests of Hypotheses that Probationer and Parolee Recidivism in The First Year of Supervision was Lower in BTC Areas than in Other Areas After BTC Implementation

Hypothesis: BTC reduced recidivism among ^a	Likelihood Any Arrest	Likelihood Drug Arrest	Number of Arrests	Number of Drug Arrests
I. All probationers and parolees:				
In BTC areas	ns	ns	ns	ns
In BTC areas with more drug tests per supervisee	ns	ns	ns	ns
In BTC areas with more sanctions per supervisee	ns	ns	ns	ns
In BTC areas with more sanctions per positive drug test	ns	ns	ns	ns
II. Probationers and parolees with drug conditions:				
In BTC areas	ns	P<.1	ns	P<.1
In BTC areas with more drug tests per supervisee	P<.05	P<.05	P<.01	P<.05
In BTC areas with more sanctions per supervisee	P<.1	P<.1	ns	P<.1
In BTC areas with more sanctions per positive drug test	ns	ns	ns	ns

a – One-tailed significance test.

BTC did not reduce arrests in the first year of supervision for the full population of probationers and parolees between March 2000 and September 2001. This finding is not surprising, given that less than half of those under supervision have a drug condition and are thus targeted for BTC intervention. The findings do indicate that arrests of probationers and parolees with drug conditions were lower as a result of BTC as follows.

- Probationers and parolees with drug conditions had a slightly, but significantly lower likelihood of arrest for a drug offense and significantly fewer drug arrests.
- In BTC areas that administered more drug tests per person under supervision, probationers and parolees with drug conditions had a significantly lower likelihood of arrest (for any offense and for drug offenses) and significantly fewer arrests (for any offense and for drug offenses).

- In BTC areas that administered more sanctions per person under supervision, probationers and parolees with drug conditions had slightly, but significantly lower likelihood of arrest (for any offense and for drug offenses) and significantly fewer arrests for drug offenses.

In general, the effects of BTC were most consistent in the area of reducing drug offenses in the first year of supervision. The third indicator of BTC implementation, the ratio of sanctions to positive drug tests, was not significant. Because positive drug tests are only one infraction, and other kinds of infractions, especially failure to appear for drug tests, are excluded, this measure may not be a very sensitive indicator of BTC sanctioning implementation. The implications of the findings are discussed in the Executive Summary, the first section of this report.

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Appendix A

Table A.1. Percentage of Offenders with Drug Conditions, by County and Time

Supervising Jurisdiction	Mar 95 – Aug 95	Sep 95 – Feb 96	Mar 96 – Aug 96	Sep 96 – Feb 97	Mar 97 – Aug 97	Mar 00 – Aug 00	Sep 00 – Feb 01	Mar 01 – Aug 01
BTC Areas								
Baltimore City	0.44	0.15	0.35	0.47	0.25	0.51	0.48	0.46
Baltimore County	0.32	0.20	0.40	0.25	0.31	0.48	0.35	0.35
Charles County	0.51	0.60	0.56	0.51	0.51	0.53	0.60	0.58
Howard County	0.31	0.39	0.40	0.45	0.44	0.38	0.49	0.48
Montgomery County	0.33	0.30	0.34	0.41	0.37	0.46	0.44	0.52
Prince George's County	0.33	0.40	0.44	0.35	0.44	0.39	0.53	0.33
Washington County	0.52	0.58	0.29	0.41	0.41	0.45	0.60	0.47
Non BTC Areas								
Anne Arundel County	0.50	0.46	0.54	0.61	0.67	0.51	0.53	0.65
Carroll County	0.24	0.30	0.44	0.38	0.44	0.42	0.44	0.37
Cecil County	0.46	0.53	0.46	0.46	0.54	0.51	0.46	0.41
Frederick County	0.49	0.57	0.47	0.59	0.52	0.45	0.56	0.65
Harford County	0.35	0.46	0.28	0.47	0.34	0.55	0.56	0.59
St. Mary's County	0.26	0.30	0.37	0.20	0.30	0.56	0.36	0.38
Wicomico County	0.36	0.36	0.26	0.39	0.43	0.30	0.28	0.43