Using Certainty and Celerity to Deter Crime[1]

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Abstract. Much of the criminal deterrence literature in economics focuses on changes in policing and sanction severity, but these guarantee neither certainty nor celerity of punishment for a violation. This paper presents an individual-level analysis of a large-scale effort to dramatically increase both certainty and celerity of sanction. South Dakota's 24/7 Sobriety Program (hereinafter 24/7) requires that alcohol-involved offenders abstain from alcohol and be tested for alcohol multiple times per day. Those failing or missing a test are subject to a swift, certain, and moderate sanction, typically a night or two in jail. Using criminal-history information for 20,243 individuals arrested for a second or third offense for driving under the influence of alcohol, this paper estimates the effect of 24/7 participation on re-arrest for any offense or having probation revoked. Exploiting variation in timing of county adoption in an instrumental variables bivariate probit model, we estimate that relative to non-24/7 participants, 24/7 reduces arrests and revocations by 13.7 percentage points (49 percent) 12 months after DUI arrest. We also detected reductions at 24 and 36 months—13.8 percentage points (35 percent) and 11.7 percentage points (26 percent), respectively. The implications of these results extend beyond reducing heavy alcohol use and alcohol-related crime; they provide evidence that it is possible to create a credible deterrent threat on a large scale by prioritizing both certainty and celerity of sanction.

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1. INTRODUCTION

The ability to deter rule violations is based on a combination of the certainty, celerity, and severity of the sanction for noncompliance (Beccaria, 1764; Bentham, 1781). With several studies finding that many individuals exhibit extraordinarily high discount rates (e.g., Ainslie and Haslam, 2002; McClure et al, 2004; McClure and Bickel, 2014), it is not surprising that recent reviews of the criminal deterrence literature argue for more emphasis on certainty and celerity rather than severity (National Research Council, 2014; Chalfin and McCrary, 2017). However, there are practical and bureaucratic barriers to observing and quickly adjudicating every rule violation in most real-world settings. Indeed, the vast majority of offenses are neither detected by nor reported to authorities (e.g., Beitel et al., 2000; Truman & Langton, 2015). This presents challenges for those tasked with monitoring the millions of individuals subject to community corrections supervision (Kaeble et al., 2016).

This paper evaluates a large-scale effort to significantly increase certainty and celerity of sanction for an offense while keeping severity low: South Dakota's 24/7 Sobriety Program (hereinafter 24/7). Beginning in 2005, South Dakota's 24/7 pilot mandated as a condition of bond that those rearrested for drunk driving must abstain from alcohol and blow into a breathalyzer once in the morning and once at night every day. Those testing positive for alcohol were immediately jailed, typically for a day or two. The program expanded geographically as anecdotes about its success spread beyond the pilot counties and state legislation began providing funding to interested counties in 2007. The program also expanded with respect to eligible offenses and alcohol detection technologies. From 2005 through February 2017, more than 30,000 unique South Dakotans participated in 24/7; this is remarkable coverage for a state with approximately 650,000 adults.[2] More than 99 percent of the breathalyzer tests were taken and passed, and for those who wore the monitoring bracelets, more than 99 percent of the monitoring days resulted in neither a confirmed drinking event nor a tampering event. Overall, these participants accumulated more than 5 million days without a detected alcohol violation, missed test, or tampering event.

Our analysis is based on 20,243 individuals who were arrested for a second or third drunk driving offense in South Dakota from 2004 to 2011. We obtained the complete criminal history

[2] As 76 percent of 24/7 participants are men, over six percent of the state's male adult population has participated in the program.

information for these individuals (including probation revocations) and determined whether they participated in 24/7 based on the program's administrative records. To estimate the causal effect of 24/7 on the probability of being arrested or having probation revoked, we use program availability in a county as an instrument for individual participation. The results show that 24/7 participation had a large effect on criminal behavior: we estimate that relative to non-24/7 participants, 24/7 reduces arrests and revocations by 13.7 percentage points (49 percent; $p < 0.01$) 12 months after DUI arrest. We also detected reductions at 24 and 36 months—13.8 percentage points (35 percent; $p < 0.01$) and 11.7 percentage points (26 percent; $p < 0.01$), respectively. These findings are robust to a number of alternative assumptions and specifications. These results provide evidence that it is possible to create a credible and effective deterrent threat on a large scale by prioritizing both certainty and celerity of sanction.

The rest of the paper is structured as follows: Section 2 summarizes the background literature, with a special focus on the origins of 24/7 and how it spread throughout South Dakota. Section 3 describes the data and empirical approach while Section 4 presents the main results robustness checks, and subgroup analyses. Section 5 offers concluding thoughts.

2. BACKGROUND

This section begins with a short summary of the research linking alcohol consumption and crime. It then highlights the research on public policies intended to reduce alcohol-involved crime, with a special focus on efforts intended to reduce alcohol-impaired driving. The final section describes the inception and growth of 24/7 Sobriety in South Dakota and reviews the existing research on the program.

2.1 Alcohol and crime

Some crimes are alcohol-involved by definition (e.g., public drunkenness, DUI). Other offenses are linked to alcohol because there is a belief by law enforcement officers, victims, and sometimes the alleged perpetrators that the crime was caused or intensified by alcohol consumption. The clinical literature overwhelmingly finds that alcohol intoxication impairs cognitive functioning, especially with respect to decision making, problem solving, and risky behavior (e.g., Peterson et al., 1990; Mosely et al., 2001). Further, there is strong experimental evidence that acute alcohol intoxication can increase aggression in some users (Bushman & Cooper, 1990).

Alcohol use is common among criminal justice populations. For example, approximately one-third of those incarcerated in state prisons self-reported alcohol use at the time of their offense (Rand et al., 2010). Victims of violent crimes reported similar rates of alcohol involvement among their offenders (30%) with substantially higher rates reported among those assaulted by intimates (66%) and spouses (75%) (Greenfeld, 1998). Not surprisingly, very high rates of alcohol use disorders have been noted among drunk drivers (Brinkmann et al. 2002; Osilla et al. 2012). For example, among first-time DUI offenders in Los Angeles, Osilla et al. (2012) estimate that more than 90% met the diagnostic criteria for past year alcohol abuse and about two-thirds met the criteria for dependence.

From a social perspective, the costs associated with alcohol-related crime are large, but hard to precisely estimate given questions about how much alcohol contributes to various crime categories. One estimate of crime-related costs of excessive drinking[3] was more than $70 billion dollars for 2006 (Bouchery et al., 2011). A more recent estimate focused only on the economic costs of alcohol-involved traffic crashes suggested they were more than $40 billion in 2010 (Blincoe et al., 2015).

2.2. Policy responses to reducing alcohol-involved crime

A variety of public policies have been implemented to reduce alcohol-involved crime and other harms associated with alcohol consumption; this paper is largely focused on the former. Carpenter and Dobkin (2012) review the literature on how five alcohol regulatory policies (tax/price restrictions, age-based restrictions, spatial restrictions, temporal restrictions, and other regulations) affected FBI Index violent and property crimes—not DUI. They concluded:

> [A]t least some of the extensively documented correlations between alcohol availability, alcohol consumption, crime, and violence do, in fact, represent true causal effects of alcohol use on crime commission. This seems especially true for interventions that induce very large and stark changes in alcohol consumption (e.g., large price or availability changes), as well as for alcohol control policies that effectively manipulate

[3] Defined as one or more of the following: "Binge drinking (4 drinks per occasion for a woman, and 5 drinks per occasion for a man); heavy drinking (1 drink per day on average for a woman, and 2 drinks per day on average for a man); any alcohol consumption by youth aged 21 years; and any alcohol consumption by pregnant women" (Bouchery et al., 2011, 517).

not only alcohol consumption but also potential and realized social interactions (e.g., mandatory closing hours and drinking ages) (323).

Effects on DUI in particular, though, are of interest. Repeat DUI offenders are responsible for a disproportionate share of DUI fatalities, injuries, and costs (e.g., Dugosh, Festinger, & Marlowe, 2013). A meta-analysis of remedial programs targeting DUI offenders—including treatment, education, psychotherapy, counselling, and contact probation—finds that they lead to at least a 7–9 percent reduction in driving under the influence recidivism and alcohol-related crashes (Wells-Parker et al., 1995). There is also long literature suggesting that drivers' license suspensions/restrictions can reduce drunk driving (See review in Rodgers, 1997). A recent review (Miller et al., 2015) was much more pessimistic, noting "a dearth of high-quality evaluations of DUI interventions" in the peer-reviewed literature; however, the authors argue "it is reasonable to conclude that evidence exists to suggest that multi-component programs (e.g., those that provide intensive supervision with treatment) are more effective than those which target only one aspect of the issue." Indeed, a systematic review of DUI-treatment courts, which typically combine long bouts of treatment with strong judicial oversight for DUI offenders, suggests they may reduce the risk of arrest for any type of offense by roughly 25 percent (Mitchell et al., 2012).[4]

To generate a better estimate on the effect of increasing sanctions on the probability of future drunk driving, Hansen (2015) uses a novel dataset of every DUI stop in Washington State from 1999-2007. Using a regression discontinuity design that exploits discrete thresholds around blood alcohol content (BAC) levels that determine standard (0.08) and aggravated (0.15) DUI offenses, he finds that the sanctions imposed at these thresholds are effective in reducing repeat drunk driving. Hansen (2015) acknowledges that the analysis cannot rule out that some of this effect may be attributable to incapacitation or rehabilitation, but a series of analyses suggest that the primary mechanism is deterrence.

[4] From Mitchell et al. (2012): "The systematic search identified 154 independent, eligible evaluations, 92 evaluations of adult drug courts, 34 of juvenile drug courts, and 28 of drunk-driving (DWI) drug courts. The findings most strongly support the effectiveness of adult drug courts, as even the most rigorous evaluations consistently find reductions in recidivism and these effects generally persist for at least three years. The magnitude of this effect is analogous to a drop in general and drug-related recidivism from 50% for non-participants to approximately 38% for participants. The evidence also suggests that DWI drug courts are effective in reducing recidivism and their effect on recidivism is very similar in magnitude to that of adult drug courts (i.e., a reduction in recidivism of approximately 12 percentage points); yet, some caution is warranted, as the few available experimental evaluations of DWI drug courts do not uniformly support their effectiveness."

An increasingly common approach to reducing repeat drunk driving is to order DUI offenders to install an ignition interlock device (IID) on their vehicles. With these devices, drivers must blow into a breathalyzer before starting the automobile and it will not start if alcohol is detected. IIDs are effective in deterring impaired driving as long as they are installed;[5] however, the bulk of the evidence suggests the IID effect quickly diminishes after they are removed from the vehicle and there is very little evidence that these devices alone reduce alcohol consumption (Willis, Lybrand, & Bellamy, 2004; Elder et al., 2011; Government Accountability Office, 2014; Voas, 2015).[6]

In the United States there is substantial focus on preventing convicted drunk drivers from *driving* drunk, but there is considerably less focus on preventing convicted drunk drivers from *getting* drunk. In some jurisdictions those arrested or convicted for DUI can be ordered to abstain from alcohol as a condition of bond or probation, but this condition is rarely enforced (Heaton, Kilmer, & Nicosia, manuscript). 24/7 changed that in South Dakota.

2.3 Swift, Certain, and Moderate Sanctions: South Dakota's 24/7 Sobriety Program

In 2003, South Dakota Governor Tim Rounds established a corrections working group focused on reducing the incarceration rate and the attendant cost of further prison construction (*Rapid City Journal*, 2003). Since alcohol-involved offenders accounted for a significant share of their prison population, South Dakota's new Attorney General, Larry Long, believed reducing alcohol consumption among individuals involved in the criminal justice system should be a priority. Long noted that many alcohol-involved offenders in South Dakota were ordered to abstain from alcohol as a condition of bond or community supervision, but this condition was not enforced (National Partnership on Alcohol Misuse and Crime, 2009). Thus, he argued that the state should implement a pilot program with DUI arrestees which combined abstinence orders

[5] The installation rates are generally low for a few reasons, including lack of enforcement and monitoring to ensure compliance, as well as the fees and penalties that offenders have to pay before they are eligible for interlock-restricted driving privileges (Government Accountability Office, 2014).
[6] It's worth highlighting two outliers in the IID literature. One study by Rauch and colleagues (2011) randomly assigned 1,927 drivers eligible for relicensure to either the two-year ignition interlock device license restriction program or the "normal and customary sanctions afforded to multiple offenders." The study found that those assigned to the ignition interlock device program still had a statistically significant reduction in the probability of an alcohol-impaired driving violation two years after the intervention. Another analysis of a four-county IID pilot program by the California Department of Motor Vehicles (2016) yielded mixed results: "There was strong evidence of a reduction in DUI recidivism, across all offender levels, among those obtaining an IID-restricted license under provisions of this law. However, there is also strong evidence of a consistent increase in crashes, including fatal/injury crashes, among these same drivers."

with twice-a-day breathalyzer tests; those testing positive for alcohol or skipping a test would be subject to a very modest sanction: a night or two in jail.

His preference to prioritize certainty and celerity of sanction over severity was consistent with principles of behavioral economics. Impulsivity is especially common among individuals who drink and drive (Sloan, Eldred, and Xu, 2014), and because severe penalties understandably require more due process and may be more costly for systems to impose, increasing severity may have the effect of reducing celerity and certainty. Also, within the clinical literature on alcohol treatment, alcohol-dependent individuals have been found to be responsive to predictable, immediate consequences for behavior (e.g., receiving a small gift in exchange for passing a breathalyzer test; Petry et al., 2000).

Long and his staff implemented the pilot—known as 24/7 Sobriety—in five South Dakota counties: the two most populous counties in the state (Pennington and Minnehaha), and three small counties (Bennett, McCook, and Tripp).[7] The choice of the specific counties was heavily influenced by personal relationships the AG and his staff had with different judges and sheriffs (Mickelson, personal communication). The pilot started in 2005 and initially targeted those arrested for a repeat DUI offense as a condition of their bond.[8] Specifically, judges in the pilot imposed two additional bond conditions on participants: (1) Defendants must abstain from alcohol, and (2) Defendants must report to a test site once in the morning and once in the evening for alcohol tests. Long (2009) reported that "Defendants who tested positive were immediately incarcerated for violating the bond condition. Bench warrants were issued for defendants who failed to report to the test site on time. All defendants who violated a bond condition were incarcerated for 24 hours before making a court appearance, where the same conditions were reimposed."

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[7] There was also a goal of getting big and small counties, and at least one that didn't have its own jail.

[8] This is similar to Hawaii's Opportunity Probation with Enforcement (HOPE) program that was independently developed in at the same time. While positive results of the HOPE randomized-controlled trial (Hawken & Kleiman, 2009; Hawken et al., 2016)—which included frequent and random drug testing with swift, certain, and short jail stays—have received tremendous attention, new results from a four-site RCT replication of HOPE were not encouraging (Lattimore et al., 2016). However, some quasi-experimental studies of supervision programs similar to HOPE—but not exact replicas—have yielded positive findings (e.g., see discussions in Kleiman et al., 2014; Hawken, 2016). Washington State implemented a program that was intended to expand the HOPE model to a broader criminal justice population throughout the entire state. Hamilton et al.'s (2016) evaluation of the effort was quite positive, but its research design (reliance on a historical comparison group) leaves open important questions about how much of the detected correlation is causal.

State and county officials believed the program worked because over 99 percent of scheduled tests were taken and passed, and the county officials also liked the program because participants paid $1 per test to a fund for the sheriff. Other counties soon began contacting the AG about participating, and by the end of 2006, residents of 25 counties were enrolled in 24/7 programs. Further expansion was spurred by a state law passed in 2007 which appropriated $345,000 and set administrative rules for program operation, and a second bill in 2008 appropriating another $400,000 in state funding for program operations.[9] Figure 1 shows how the program spread throughout the state.

[Insert Figure 1 here]

The program also expanded in terms of eligible offenses and testing technologies. Table 1 shows the distribution of offenses for 2006 and 2015. DUI has always accounted for the majority of cases, but there was a significant increase in non-DUI offenses over time. In 2006, the AG's office introduced the use of continuous alcohol monitoring ankle bracelets which participants can wear for months at a time, even in the shower.[10] Every 30 minutes the device tests the participant for alcohol and it can also determine whether someone has tampered with the device. Initially this information was relayed to a private company via a modem in the individual's home, but over time more participants just came into the sheriff's office once or twice a week to upload the information from the bracelet to the private company. To date, the majority of 24/7 participants in South Dakota are monitored via twice daily breathalyzers; in 2015, 21 percent of participants wore the ankle bracelets.[11]

[Insert Table 1 here]

The duration of 24/7 participation is not fixed and judges may keep participants in the program longer if they are struggling. It is not uncommon for someone to start on the program pre-trial and continue post-conviction. In our analytic data set, the median number of days for

[9] Testing for illegal drugs is part of the program, but this is heavily concentrated in a small number of counties.
[10] Decisions about whether someone tested twice a day or wore a bracelet were ad hoc: in some rural areas it was infeasible for someone to drive in twice a day, and in some cases judges would put people on the bracelet if they did not perform well with the twice a day testing. In other places, participants who preferred to wear the bracelet and could afford it (daily costs were $6 instead of $2) could receive that option if there were bracelets available. The AG purchased the bracelets and was in charge of distributing them throughout the state.
[11] The state began piloting twice-per-day testing via IID in October 2012 and had 350 IID participants by June 2015.

participants on the alcohol monitoring bracelet exceeds the median for twice-daily participants (180 versus 109),[12] but these figures tell us nothing about the relative efficacy. For example, it could be the case that those who know they are going to be on the program for a short period are more willing to submit to twice-daily tests than those who know they will be on the program for an extended period (e.g., if they lost their license because of a DUI and would like a restricted permit to drive to work, which requires 24/7 participation).

Fifty-three percent of participants make it through the program without a violation (i.e., a failed or missed test), 19 percent violate once, 11 percent violate twice, and about 17 percent violate three or more times. Judges decide when someone is terminated from the program and these individuals are generally returned to jail for violating their conditions of bond or probation. Violations are always supposed to be sanctioned with jail time (South Dakota AGO, Undated), ranging from 12-72 hours behind bars (Midgette, manuscript). Systematic data on repercussions for 24/7 violations do not exist as violations are neither criminal nor civil offenses and do not appear on rap sheets. However, state guidelines and trainings call for immediate incarceration for alcohol-positive participants and those who miss a test. Based on information gathered from field studies of eight sites that account for nearly 80 percent of participants, sites routinely hold violating participants for a short period in a cell after an in-person alcohol violation and on next contact after notifying participants of non-compliance by phone after remote alcohol monitoring violations and no-shows (Midgette, manuscript). Some counties have also adopted standardized graduated sanctions for violations, e.g., a 12-hour hold for the first violation and 24 hours for the second.

Through February 2017, more than 30,000 unique South Dakotans have participated in 24/7 and have accumulated more than 5 million days without a detected drinking event (authors' calculations).[13] To be clear, 5 million days without a drinking violation does not imply 5 million days without *any* drinking because alcohol passes through the system relatively quickly and the

[12] Participants' days monitored in the analytic dataset for this analysis are greater than figures published in prior analyses of South Dakota 24/7 Sobriety for a combination of reasons. First, restricting observations to individuals that began the program at least six months prior to the data end date, so reducing bias toward zero in the statistics due to right censoring. Second, restricting observations to first-time enrollment removes potential erratic enrollee entries from multiple testing sites under separate participant IDs. Finally, first-time participation typically is longer in duration than subsequent spells, in part due to higher risk of removal for multiple-enrollees due to higher rates of re-arrest or poor program performance.

[13] Through September 2016 there were over 8.8 million breathalyzer tests and the pass rate exceeds 99% (with no-shows in the denominator). SCRAM participants accumulated 6,434 violations over 1.55 million days of monitoring, equivalent to at least a 99.6% daily compliance rate.

testing media have limited sensitivity. If someone passes a breathalyzer test at 8am, they can theoretically have a few drinks and still test negative for alcohol again that evening. Also, the alcohol monitoring bracelets may not detect alcohol consumed slowly throughout the day. While these individuals are technically ordered to abstain from alcohol, the program's testing is largely focused on reducing heavy drinking and its associated outcomes.

As 24/7 was being implemented in South Dakota, there were other interventions being adopted throughout the state that may have also influenced alcohol-related driving outcomes. Long et al. (2009) note that in 2006 the state repealed its implied consent law, and around the same time the state revised the educational programming for those convicted of their first DUI. In addition, the authors report that there was increased DUI enforcement (e.g., sobriety checkpoints), an increase in media campaigns targeting impaired driving, and the implementation of a new program targeted at parents to help reduce underage drinking.

To help isolate the effect of 24/7, Kilmer et al. (2013) exploited county-level variation in implementation dates (see Figure 1) to assess the effect on five county-level outcomes: first time DUI arrests, repeat DUI arrests, domestic violence arrests, total traffic crashes, and traffic crashes involving males 18-40. Using county-level and year-month fixed effects as well as several county-level control variables (at the month and annual levels), they found that after 24/7 was operational at the county level, repeat DUI arrests dropped 12 percent, and domestic violence arrests dropped 9 percent. There was no evidence that the program influenced the number of first-time DUI arrests or total traffic crashes. In the main specifications, 24/7 was defined as operational once the number of county residents in 24/7 for a given month equaled or exceeded 25 percent of the number of driving under the influence arrests in the county, where the latter is defined as the county's moving monthly average during the previous year to address any seasonality. If one used a less conservative threshold of 10 percent, the reduction in the number of repeat DUI arrests at the county level changed from 12 percent to nearly 18 percent.

Subsequent research using a similar research design found that implementation of 24/7 was associated with a 4% reduction in all-cause adult mortality, concentrated among circulatory and injury-related deaths (Nicosia, Kilmer, & Heaton, 2016). Another aggregate-level analysis using the National Incident Based Reporting System and a triple-difference methodology for a limited set of counties provides additional support for the efficacy of 24/7 in South Dakota (Heaton, Kilmer, & Nicosia, manuscript).

Thus far, however, there have been no peer-reviewed studies of South Dakota's 24/7 Sobriety Program using individual-level data. An obvious concern with community-level analyses is that it limits the ability of researchers to identify the causal mechanisms driving the observed change (e.g., general versus specific deterrence). Further, policymakers want to know what the individual-level effect of 24/7 is so they can make comparisons with other well-studied programs targeted at the same population, such as DUI courts and IID (see review in Section 2.2).

A report by Loudenberg et al. (2012) sought to assess the effect of 24/7 on the time until next DUI arrest by comparing a sample of 24/7 participants from 2005-2010 with a matched sample of "non-program participants who were arrested in 2003, 2004, or 2005 and who did not participate in the 24/7 Sobriety Program for the DUI offense on the docket" (p. 25). The differing time periods for the survival analysis raise concerns that the risk of arrest could have been much different for the treatment and control groups (and there is no attempt to control for this). In addition, there are also important selection issues: Those in the treatment group were limited to those who were in 24/7 for at least 30 days.[14] While the authors conclude that "the long-term effects of the 24/7 Sobriety Program upon DUI offense recidivism is well supported" (p. 27), we offer a more conservative and defensible modelling strategy.

3. Data and Methods

This paper contributes to the deterrence literature by estimating the causal effect of 24/7 participation on criminal recidivism using individual-level data and program availability as an instrumental variable. *A priori*, we expect the deterrent effect of 24/7 participation on criminal behavior to diminish as the time after participation elapses.

3.1 Data

This analysis uses criminal records data for 20,243 individuals arrested for a second or third offense for DUI (DUI-2 and DUI-3, respectively) in South Dakota between 2004 and April 2012 from the South Dakota Attorney General's Office. These data include both 24/7 participants and those who never participated in the program.[15] Each county enters information

[14] The report also included a different analysis which compared any twice-daily breathalyzer participants with anyone who was arrested for a DUI offense. There did not appear to be any attempt to match the samples (other than on DUI offense arrest) or control for covariates which could influence the probability of re-arrest.

[15] We do not consider DUI-3 arrestees who had previously been on 24/7 since re-enrollment is necessarily a consequence of rearrest, thus creating an endogeneity problem. Additionally, prior exposure to the program may

about 24/7 participants and their testing results into the Attorney General's statewide 24/7 database. We obtained participant-level data dating back to the original pilot in 2005.

We do not have information about all crimes committed by DUI arrestees; thus, we rely on administrative information about arrests and probation revocation. As alcohol influences a wide array of criminal behaviors, we consider any offense in the main runs, not just those specifically associated with alcohol, such as DUI or public drunkenness. Since some of the individuals in both the control and treatment groups are on probation, it is possible that their probation officer will seek to revoke probation for a crime instead of making a new arrest. While probation revocation is uncommon in our analytic sample, it is appropriate to incorporate that information into a dependent variable that serves as a proxy for criminal behavior.[16]

To control for time-varying socioeconomic conditions in each county, we include the non-seasonally adjusted unemployment rate from the Bureau of Labor Statistics (2015). We also include per capita rates of county-level sworn law enforcement officers per ten-thousand residents as a proxy for local-level changes in law enforcement (FBI, 2014), county-year per capita rates of on- and off-premises alcohol outlets provide a measure of alcohol availability (U.S. Census Bureau, 2017).

3.2 Empirical Approach

Judges, probation officers, and parole officers have discretion about who ends up in the 24/7 program. Some participants enter the program as a condition of bond, some as a condition of probation, some participate to obtain a restricted driver's license (which allows them to drive to work), and some participate in multiple settings (i.e., pre- and post-conviction). Days on the program can vary dramatically depending on the time between arrest and disposition, and sometimes participants will be ordered to stay on the program longer if they violate the program. There is tremendous variation at which point in the process individuals are ordered to participate, especially in the earlier years.

The lack of uniformity creates challenges for evaluation. If one defines the treatment beginning after the first test, then how does one define the control group and determine when to start measuring the time at risk? To address this issue we employ an approach that biases our results toward not finding an effect: If anyone is tested as part of the 24/7 program after an arrest

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differentially affect the deterrent power we seek to measure. Omitted DUI-3 participants previously assigned to 24/7 for a DUI-2 offense are included in the sample using that initial DUI-2 participation spell.

[16] We consider analyses that exclude probation information in the sensitivity analysis.

for DUI-2 or DUI-3—even if they eventually drop out of the program after a couple of days—we consider them treated. This ITT approach is conservative for multiple reasons. First, those who are in the program for a short amount of time would not be expected to yield benefits, and so this should dilute the treatment effect. Second, if someone was arrested for DUI-2, released on bond, and arrested for something else before entering 24/7, our approach would attribute that failure to 24/7 even though the individual had not yet started the program. Third, if judges or probation officers ordered some DUI-3s to 24/7 in lieu of jail, then the controls in jail would be incapacitated and not at risk for being arrested for a new crime. Thus, our approach is conservative against finding an effect.

Table 2 displays the descriptive statistics for the 24/7 participants and non-participants in the sample. Approximately three-quarters of the sample are men, and arrestees average three prior offenses (median=2). By most observable individual and community level measures that may be potential confounders, participants and their comparison group are similar in aggregate. The median time between the index DUI arrest and the prior DUI is 7.5 percent longer for the 24/7 group, though the mean is nearly identical.

[Insert Table 2 here]

Probit. We first estimate probit models to understand what factors predict re-arrest/revocation within a 12, 24, and 36-month time frame among DUI-2 and DUI-3 offenders combined. The probability of re-arrest is estimated using Equation (1):

$$(1)\ P(A_{ict}) = \beta_0 + \beta_1 24/7_i + \beta_2 X_{ict} + \alpha_c + \alpha_t + \varepsilon_{ict}$$

where the probability that an individual is rearrested within a fixed time horizon (A_{ict}) is a function of 24/7 enrollment ($24/7_i$), vectors of individual- and county-level characteristics (X_{ict},), county fixed effects (α_c) which remove any time-invariant unobservable differences across counties, and time fixed effects (α_t) based on the month and year when each DUI arrest occurred (e.g., January 2004, February 2004, etc.).

The criminal history characteristics include separate indicators of prior arrest for violent crime, drugs, or illegal weapons; it also includes an indicator for DUI-3 (vs. DUI-2). As time since last DUI is correlated with future reoffending, we use decile buckets based on the complete analytic sample used in our main results for the time in days between an arrestee's prior DUI and the DUI serving as the starting point for measurement in the present analysis (e.g., days between DUI-1 and DUI-2 for DUI-2 arrestees). We flexibly account for the relationship between unobserved individual characteristics proxied for by the count of days between prior DUI offenses and the outcome of interest by employing decile bucket dummies rather than prescribing a shape to the relationship.

Seemingly unrelated bivariate probit. Any adult repeat-DUI arrestee in a county with an active 24/7 program is eligible for enrollment but not all such arrestees are enrolled. Over our sample set, the share of DUI-2 and DUI-3 arrestees in counties with 24/7 who entered the program increased from 27.7 percent in 2006 to 38.6 percent in 2011. The discretion that judges and probation officers have raises the issue of selection bias; however, the direction of the bias is unclear. In some cases individuals who are most likely to recidivate could be ordered to the program because they need the most help; in other cases sympathetic judges and probation officers may only select those believed to have the best chance at success in the program. We also must consider the observed selection that occurs when DUI offenders choose to participate in 24/7 as a condition of receiving a restricted driver's license that only allows them to drive to work.[17]

We attempt to account for this by using an instrumental variable (IV) bivariate probit approach. Ideally, the instrumental variable will predict enrollment in 24/7 without being correlated with the residual error. In this case, we exploit the variation in the timing of 24/7 implementation across counties. Specifically, we construct our instrument as an indicator for whether the county of the individual's arrest had an operational 24/7 program (which Kilmer et al. (2013) defined as the number of 24/7 participants in any given month equaling or exceeding one-quarter of the 12-month moving average count of DUI arrests in that county). We estimate the probability of re-arrest ($P(A_{ict})^*$) by solving two equations simultaneously:

$$(2)\ 24/7_i^* = \gamma X_{ict} + \delta Z_{ct} + \alpha_c + \alpha_t + u_{ict}$$

$$(3)\ P(A_{ict})^* = \beta_0 + \beta_1 24/7_i + \beta_2 X_{ict} + \alpha_c + \alpha_t + \varepsilon_{ict},$$

$$\text{where } 24/7_i\text{=1 if } 24/7_i^* > 0,\ 24/7_i\text{=0 if } 24/7_i^* \leq 0$$

The model is identified using the instrument (Z_{ct}) in addition to the covariates, —X_{ict}, α_c, and α_t—defined in Equation (1). We simultaneously estimate the probability of re-arrest $P(A_{ict})$ based on the endogenous variable program participation ($24/7_i^*$), and the other covariates. We assume

[17] An unknown share of DUI offenders choose to drive even though their driver license is revoked.

that ε_{ict} and u_{ict} are distributed bivariate normal, such that $E[\varepsilon_{ict}] = E[u_{ict}] = 0$, $var[\varepsilon_{ict}] = var[u_{ict}] = 1$ (Greene, 2011). Thus, our bivariate probit approach allows inference of the average treatment effect among the repeat DUI offenders.

Monotonicity is likely satisfied as the probability of assignment to 24/7 is always positively related to the program's availability in the county where an individual is arrested or resides. The independence assumption underlying our instrument requires that the timing of a county's implementation is not due to individuals' future recidivism risk, and that the expansion of 24/7 over time is not related to re-arrest rates within counties. To help test this assumption, we compare repeat-DUI arrest rates in pilot and non-pilot counties in the pre-program period. Figure 2 shows the indexed rate of repeat-DUI per capita for the five-year periods before and after the 2005 rollout of the program. Since the program began as a pilot but was adopted throughout the state over time, implementation is represented as a gradient box, where the darker shaded period beginning in January 2005 indicates the program running strictly in the pilot counties. There is no evident difference between DUI rates in the period preceding implementation. However, there is a notable visual gap between the pilot and non-pilot counties in the period when the program was concentrated in the few pilot counties, echoing the findings of county-level effectiveness in Kilmer et al. (2013). This gap dissipates over time, likely because other counties began utilizing the program.

[Insert Figure 2 here]

4. RESULTS

4.1. Main Results

Figure 3 plots the survival curves for 24/7 participants and those in the control group. These unadjusted data suggest that the time until next arrest or probation revocation is longer for 24/7 participants than non-participants ($\chi^2 = 90.98$, $p < 0.01$).

[Insert Figure 3 here]

Table 3 presents the results of probit models which examine the probability of being arrested for a new offense after 12, 24, and 36 months. Model 1 includes county-level controls but no criminal history information, Model 2 adds decile buckets for the number of days between the preceding and index DUI arrest, and Model 3 adds indicator variables for the number of priors in each criminal history, collapsing all larger quantities at 10 due to sparseness, and indicators for prior violent crime and drug arrests. The coefficient on the 24/7 participation variable is negative and statistically significant in all models, suggesting that the program is associated with a reduction in the probability of being arrested or having probation revoked. In the base specification (Model 1) these 24-7 participants were 10.7 percentage points ($p < 0.01$) less likely to arrested/revoked 12 months after DUI arrest. We also detected reductions at 24 and 36 months—8.9 percentage points (p < 0.01) and 7.3 percentage points (p < 0.01), respectively. The absolute value of the marginal effects in the full specification (Model 3) is slightly smaller for all three time periods, but still statistically significant at the 0.01 level.

[Insert Table 3 here]

To address the concerns with selection, we estimate instrumental variable (IV) bivariate probit models, where our binary instrument equals 1 if the 24/7 program was operational in that county at the time of the initial arrest. The F-test statistic associated with the coefficient on the active 24/7 program indicators are consistently large, and the estimated coefficient itself is positive and significant (p < 0.001), indicating the presence of an operational 24/7 program in a county is a strong predictor of assignment to the program (See Appendix B).

The structure of Table 4 mimics Table 3, except we are now focused on the IV models. The full model in Table 4 (Model 3), our preferred specification, indicates that relative to non-24/7 participants, 24/7 reduces arrests and revocations by 13.7 percentage points (49 percent) 12 months after DUI arrest. We also detected reductions at 24 and 36 months—13.8 percentage points (35 percent) and 11.7 percentage points (26 percent), respectively. While the IV coefficients are 29%-43% larger than those generated from the probit models, the difference in estimates is not statistically significant based on a z-test of coefficient equality.[18] The notion of policy exogeneity is corroborated by the consistent finding that the residuals of the instrument and policy estimations are uncorrelated for the bivariate probit models (as denoted by the model

[18] Using $z = \frac{\beta_{probit} - \beta_{biprobit}}{\sqrt{se^2_{probit} + se^2_{biprobit}}}$, the z-statistic is between 0.877 and 1.074.

ρ-statistic; see Appendix B), indicating the instrument and policy equations are independent (Wooldridge, 2002).

[Insert Table 4 here]

4.2. Robustness Checks

Table 5 displays the results of various robustness checks. For comparison purposes, Panel A includes the baseline IV bivariate probit results from Table 4. The first alternative scenario (Panel B) limits the analytic sample to those with 36 month follow-up data, allowing us to examine a consistent sample of arrestees over all four time periods. Since ending the sample at April 2009 instead of October 2011 reduces the sample size for the 12 month analyses by about 24 percent, we would expect the results to become less precise; however, the absolute value of the marginal effect become slightly larger for the 12- and 24-month runs.

[Insert Table 5 here]

Panel C limits the 24/7 treatment group to those who were only in the program for two years or less. The motivation for this scenario was to assess whether our baseline results were being driven by those who participated for more than two years. The results are more precise, and the absolute value of point estimates are marginally larger, suggesting long-term participants do not drive the results.

Panels D and E explore what happens when we add new variables to the model. In Panel D we control for whether the individual was convicted for the DUI arrest that got them into the program, and in Panel E we control for the number of days the person was incarcerated for convictions on the DUI arrest (days sentenced minus days suspended + 1, then log-transformed to account for skewness). Neither of these additions make a substantive difference.

Our baseline runs focus on whether 24/7 influences the probability of being arrested for a new offense after a DUI arrest or having probation revoked. Panel F explores the effect of excluding the probation information and only focusing on time of arrest. The absolute values of the effects sizes become somewhat smaller across the three time periods, but all remain statistically significant. This is not surprising since ignoring probation revocations biases our results toward not finding an effect of 24/7 on criminal behavior.

Panel G shows results from models omitting controls based on past criminal history information except days between prior DUI arrests. This should be insightful to researchers who have access to DMV records but not criminal history information. The results remain virtually unchanged, suggesting that it is not critical to include the rap sheet data when you have time since last DUI; however, if researchers only rely on DMV data they cannot examine whether 24/7 or another intervention influenced crimes not related to driving.

Our preferred specifications use seemingly unrelated bivariate probit models to address selection issues related to 24/7 participation. In this situation, some researchers have argued that it may be better to use two-stage residual inclusion in which first-stage residuals are included as additional covariates in the second stage (Terza et al., 2008). Panel H displays the results for this alternative approach. While the absolute values of the marginal effects get slightly smaller for the 12- and 24-month runs (-0.107 vs -0.137 and -0.112 vs -0.138, respectively), they still remain statistically significant. The effect for 36 months is almost identical, but is now only significant at the 0.05 level.

Finally, in Panels I and J, we test the sensitivity of our results to alternative definitions of when 24/7 is considered operational in a county. Recall that our main specification considers 24/7 operational when the number of 24/7 participants in any given month equaling or exceeding 25% of the 12-month moving average count of DUI arrests in that county. When we use a less conservative 10% threshold, the effect becomes somewhat larger. With the more conservative 40%, the effect is smaller and less precise, but remains substantively similar.

4.3 Subgroup analyses

This section presents the results of various subgroup analyses intended to help us get a better understanding of the causal mechanisms driving our main results. Table 6 presents results from our preferred IV specifications separately for DUI-2 and DUI-3 arrestees. On average, we would expect DUI-3 offenders to have more problems with alcohol than DUI-2 offenders. Thus, if 24/7 is significantly reducing alcohol consumption for participants, we'd expect to see less drinking and, thus, less criminal activity from DUI-3 arrestees compared to those who had only been arrested for DUI twice.

[Insert Table 6]

At 12 months after DUI arrest, the coefficient on 24/7 is negative and statistically significant ($p < 0.05$) for both DUI-2 and DUI-3 arrestees. The coefficients remain negative for DUI-2 at 24 and 36 months, but they become less precise and no longer statistically significant. The story is much different for DUI-3s where the coefficient remains negative and statistically significant at 24 and 36 months. These results are consistent with the hypothesis that 24/7 reduces alcohol consumption and had a larger effect on criminal behavior of those with more serious alcohol problems.

The fact that the coefficients indicate a longer-lasting effect of 24/7 for DUI-3s may be due to their longer participation: the median time on the program is more than 40 percent longer for them compared to DUI-2s. However, this is not necessarily the reason for the stronger effects. Participation length may be extended for those who are not doing well in the program (and shortened for those doing well) based on testing violations, but have not been arrested so remain under monitoring rather than incarcerated. That said, our main results, robustness checks, and this analysis are consistent with the contention that the effect of 24/7 on criminal activity extends beyond the time the individuals are in the program—especially for DUI-3s.

While Tables 3-6 focused on the probability of any type of arrest or probation violation, Table 7 looks at the effect of 24/7 on various types of arrests: DUI, violent crime, and property crime. Looking exclusively at the next recorded arrest to avoid confounding due to competing risks, of the 8,430 arrests observed in the three-year sample, 4,726 (56 percent) were for a subsequent DUI, 526 (6.2 percent) were for a violent crime, and 559 (6.6 percent) were for a property crime.[19] If 24/7 is reducing criminal activity via a reduction in alcohol consumption, we would expect to see larger effects for crimes with a stronger connection to alcohol. Thus, we hypothesize that the effect would be largest for DUI and this is what we observe. The marginal effect sizes are smaller in absolute magnitude for violent arrests, but all negative and the -2.6

[19] Based on FBI definition of violent crime as crimes that threaten, attempt, or actually use physical force against a person as assault, homicide, kidnapping/abduction, robbery, and forcible sex offenses, we define violent crime arrests we use the four-digit National Crime Information Center (NCIC) Uniform Offense Classification Codes, to define "violent" crimes as those with the first two digits "09", "10", "11", "12", and "13". Property crimes were defined as theft, burglary, larceny, destruction of property, vandalism, and arson.

percentage point (9.5 percent) effect at 12 months has a p-value < 0.10. The effects for property crime are very imprecise and much closer to 0.

[Insert Table 7]

5. CONCLUDING THOUGHTS

While there is strong agreement that we should not depend on increasing severity to produce criminal deterrence (Chalfin & McCrary, 2017), there is less agreement about how to best incorporate certainty and celerity, especially in the case of community corrections. South Dakota's 24/7 Sobriety Program prioritizes certainty and celerity by requiring that alcohol-involved offenders abstain from alcohol and be tested for alcohol multiple times per day. Those failing or missing a test are subject to a swift, certain, and moderate sanction, typically a night or two in jail.

Using variation in the timing of 24/7's implementation across counties in an instrumental variables bivariate probit model, we find strong evidence that 24/7 participation reduced criminal activity. While this is not surprising given previous community-level analyses of the program, the magnitude of the individual-level effect and the fact there appears to be a residual effect beyond the period of participation are particularly noteworthy. In addition, South Dakota's 24/7 program is especially attractive from a public budgeting perspective since its fiscal costs are covered by participant fees (Midgette, manuscript)[20] and does not require treatment participation or any other formal programming.

Since 24/7 was widely adopted in South Dakota and county-level analyses have been published, we can work backwards from these figures to assess the plausibility of our individual-level results. Kilmer et al. (2013) conservatively estimated that county-level adoption of 24/7 was associated with a 12 percent reduction in repeat DUI arrests at the county level (they found no effect on first-time DUI arrests). But as noted earlier in the text, only about one-third of DUI-2 and DUI-3 arrestees in counties with operational 24/7 programs end up participating in 24/7 (27.7 percent participated in 2006 and this increased to 38.6 percent in 2011). If we assumed

[20] Counties with few participants may run short-term fiscal deficits when per-participant revenue fails to cover fixed costs. However, the state also produces revenue for each participant enrolled. The program maintains an official mechanism by which they reimburse counties that demonstrate operating losses or need for infrastructure improvement related to the 24/7 program.

that tripling the participation rate to 100% would triple the effect size, we would conclude that full participation by DUI-2 and DUI-3 arrestees would be associated with a 36 percent reduction in repeat DUI arrests.[21] This conservative 36 percent reduction is in the same ballpark as the reductions in DUI arrests at 12 and 24 months reported in Table 7, which correspond to 34 to 57 percent reductions; thus suggesting our causal estimates are in-line with other analyses using different data and methods. This also suggests that most of the county-level association estimated by Kilmer et al. (2013) is through specific rather than general deterrence.[22]

It is important to stress that 24/7 does not require participants to enter treatment or engage in other services; this seems to be largely a deterrent effect, although one mechanism through which that deterrence might work is giving participants a reason to seek out treatment on their own, whether paid professional treatment or self-help (e.g., Alcoholics Anonymous). While we cannot make direct comparisons, a systematic review of DUI-treatment courts—which are much more resource intensive than 24/7 and spreading throughout the country—suggests they may reduce the risk of arrest for any type of offense by roughly 25 percent (Mitchell et al., 2012).[23] Our 24/7 results for DUI-3 arrestees are definitely in the same ballpark (12 months=52 percent; 24 months=38 percent; 36 months=33 percent). It would be extremely informative to randomly assign repeat DUI offenders to 24/7 or to another intervention (e.g., DUI Court or IID) and compare the costs and benefits of these approaches (including effects on non-driving related

[21] Of course, we must acknowledge that there were some DUI-1s, DUI-4s, and DUI-5s in 24/7, but they accounted for a small share of total DUI participants in the early years of the program (See Table 1).

[22] We cannot rule out the possibility of some small general deterrent effect. Given our research design, if there is spillover effect of 24/7 onto non-participants, it would moderate the effect size we see in models that do not account for program availability, and, implicitly, would-be drunk drivers' knowledge of the program's use in their county. Our instrument explicitly accounts for program availability. Given the marginally larger effects estimated by the instrumented model over the probit estimates, this is a possibility. Alternatively, the difference in effect magnitudes may be capturing unobserved participant characteristics that are associated with higher re-arrest risk. These possibilities are not mutually exclusive.

[23] Note that some proponents of DUI courts like to focus on what they call "Top Courts" that have a better recidivism rate. A one-page factsheet from the National Center for DWI Courts (2016) notes that "Top DWI courts reduce recidivism by 60%" which is sourced with the same Mitchell et al. meta-analysis; however, the word "top" does not appear in the Mitchell et al. article. Mitchell et al. noted that three of the four experimental evaluations of DWI courts yielded positive results and by excluding the other experimental study raises the mean odds-ratio from 1.27 (CI: 0.87-1.85) to 1.58 (0.99 to 2.54). They conclude that "[W]e we characterize the evidence as cautiously supporting the effectiveness of DWI drug courts, because while quasi-experimental evaluations find strong and consistent indications that these programs reduce general and drug related recidivism, randomized experimental evaluations find a small, non-statistically significant reduction in recidivism. Yet, the findings from experimental evaluations of DWI drug courts are ambiguous in that the majority of these evaluations find positive effects but a single, influential evaluation with negative findings heavily influences the mean effect. Clearly, only additional evaluations using experimental methods can definitively resolve the remaining ambiguity surrounding the effectiveness of DWI drug courts." Given the results of this 24/7 evaluation, we hope these future DWI Court experiments will include a 24/7 option.

outcomes). Additional insights about the long-term and dose-response effects of 24/7 could be obtained by randomly assigning 24/7 participants to different times on program.

There are also questions about whether 24/7 can work outside of South Dakota. The program has now been implemented in a number of jurisdictions throughout the country, with large state programs starting in North Dakota in 2008 and Montana in 2010. Non-peer reviewed studies of the programs in these two states are promising (Kubas, Kayabas, & Vachal, 2015; Midgette & Kilmer, 2015; Midgette et al., under review), but there is a real need for experimental research to be conducted in urban areas outside of the Great Plains.

While our results on criminal recidivism are striking, their importance extends beyond how we address DUI offenders. The growing bipartisan support for reducing reliance on long prison sentences to address nonviolent crime (e.g., Harris, 2015; Steinhauer, 2015), suggests there will be more reliance on probation and other forms of community supervision. Advances in technology will continue to make it easier and cheaper to monitor and detect violations (e.g., substance use, curfews, other place-based restrictions, interactions with others under community supervision, and possibly even firearm usage[24]), but the ability to deter violations depends on how this information is used. To this end, increasing certainty and celerity of a low severity sanction offers a promising approach for these opportunities.

[24] E.g., Loeffler (2014) demonstrates the feasibility of using wearable accelerometers to detect signals that correspond to firearm usage.

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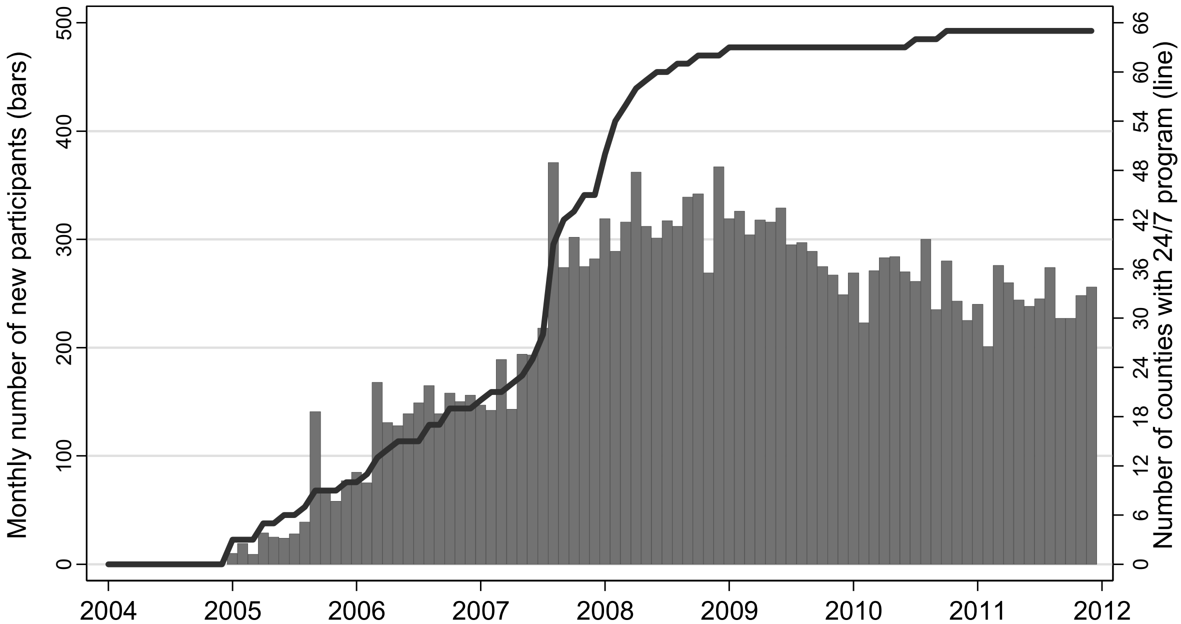
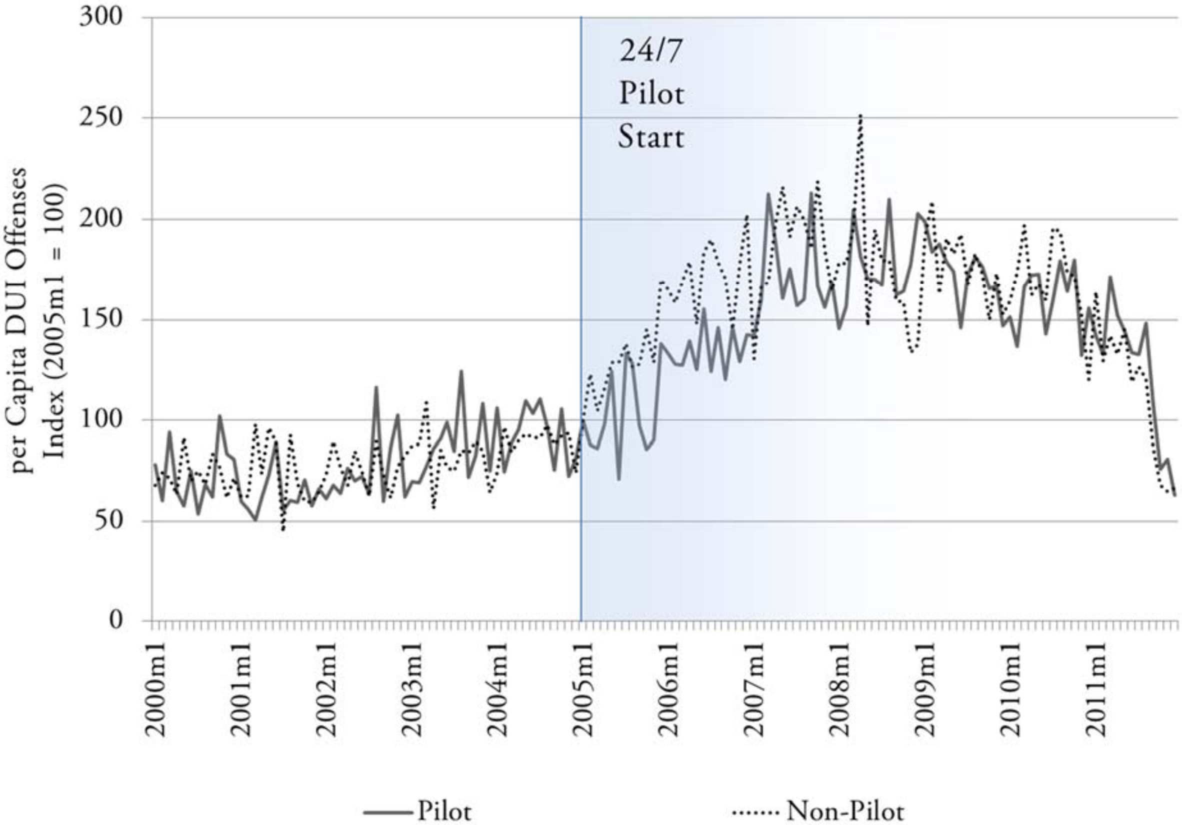
Figure 1. Growth of 24/7 Sobriety in South Dakota



Note: We define 24/7 as operational in each county once the number of county residents in 24/7 for a given month equals or exceeds a quarter of the number of DUI arrests in the county, where the latter is defined as the county's moving monthly average during the previous year to address any seasonality.

Figure 2: Comparison of pilot and non-pilot counties before and after 24/7 implementation



Note: This chart is only based on repeat-DUI arrests. The pilot included five counties; the non-pilot counties grew over time to include 60 of a possible 61 defining participation by county of residence.

Figure 3: Kaplan-Meier survival functions

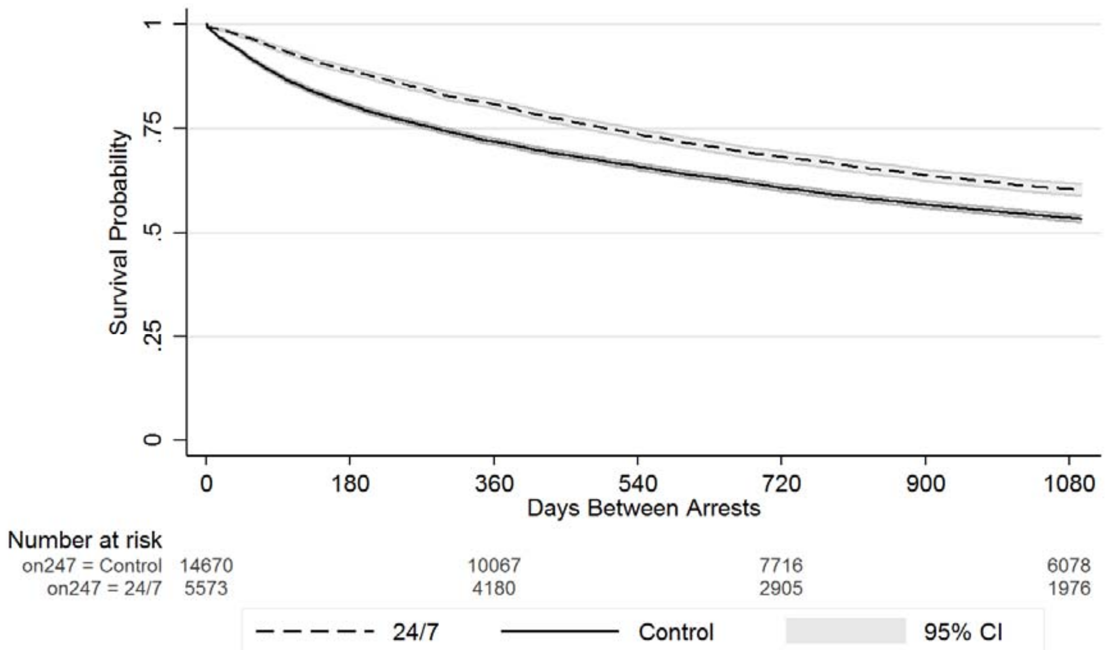


Table 1. Distribution of 24/7 offenses, 2006 & 2015

	2006		2015	
	#	%	#	%
Assault	129	7.2	699	12.9
Community Corrections Provision	49	2.7	408	7.5
Crimes against Children	7	0.4	91	1.7
DUI 1st	72	4.0	588	10.9
DUI 2nd	614	34.4	915	16.9
DUI 3rd	434	24.3	446	8.2
DUI 4th	109	6.1	157	2.9
DUI 5th and above	20	1.1	102	1.9
Domestic Violence	18	1.0	70	1.3
Drug Offense	59	3.3	1219	22.5
Theft and Burglary	23	1.3	103	1.9
Other	252	14.1	614	11.3

Table 2. Covariate summary statistics

		Control	24/7
County-level characteristics			
Sworn Officers per Capita		17.0	17.2
Package Stores per Capita		4.5	4.4
Bars per Capita		1.5	1.2
Unemployment rate (%)		3.7	3.8
Individual-level characteristics			
DUI-2 Arrestee (%)		69.6	61.9
DUI-3 Arrestee (%)		30.4	38.1
Male (%)		77.5	73.6
Age (Years)		32.8	32.7
Priors arrests			
	Mean	3.0	3.0
	Median	2	2
Days since last DUI			
	Mean	1101	1136
	Median	821	883
Violent prior (%)		17.7	16.8
Drug prior (%)		6.8	7.0
Days from arrest to 24/7 entry			
	Mean		57.9
	Median		16
Days in 24/7			
	Mean		331.6
	Median		189
N		14670	5573

Table 3. Marginal effect estimates of 24/7 on recidivism for probit models

	(1)		(2)		(3)		N
Time to re-arrest							
1 year	-0.107	***	-0.105	***	-0.097	***	19,114
	(0.012)		(0.012)		(0.012)		
2 years	-0.089	***	-0.087	***	-0.079	***	16,882
	(0.011)		(0.010)		(0.010)		
3 years	-0.073	***	-0.072	***	-0.067	***	14,513
	(0.014)		(0.012)		(0.012)		
Controls							
County and month fixed effects	Yes		Yes		Yes		
Age and gender	Yes		Yes		Yes		
County-level controls	Yes		Yes		Yes		
Previous DUI interval	No		Yes		Yes		
Detailed criminal history	No		No		Yes		

Notes: * denotes statistical significance at the 10 percent level, ** the 5 percent level, and *** the 1 percent level. The control variables for all models include gender, age, categorical indicators for number of prior arrests (top-coded at 10), indicator for DUI-3 (vs. DUI-2), indicators for violent and drug prior arrests, indicators for observation's decile rank for days between prior DUI offenses, and county-level police per capita, bars per capita, liquor stores per capita, unemployment, county and month fixed effects. Standard errors in parentheses.

Table 4.
Marginal effect estimates of 24/7 on recidivism for bivariate probit models

	(1)		(2)		(3)		N
Time to re-arrest							
1 year	-0.149	***	-0.134	***	-0.137	***	19,119
	(0.053)		(0.051)		(0.044)		
2 years	-0.158	**	-0.134	**	-0.138	**	16,886
	(0.069)		(0.065)		(0.056)		
3 years	-0.133	***	-0.109	**	-0.117	***	14,517
	(0.056)		(0.051)		(0.045)		
Minimum F-statistic on instrument	42.52	***	42.70	***	43.10	***	
Controls							
County and month fixed effects	Yes		Yes		Yes		
Age and gender	Yes		Yes		Yes		
County-level controls	Yes		Yes		Yes		
Previous DUI interval	No		Yes		Yes		
Detailed criminal history	No		No		Yes		

Notes: * denotes statistical significance at the 10 percent level, ** the 5 percent level, and *** the 1 percent level. An indicator for operational 24/7 program in county and month of arrest event is used to instrument 24/7 enrollment. The control variables for all models include gender, age, categorical indicators for number of prior arrests (top-coded at 10), indicator for DUI-3 (vs. DUI-2), indicators for violent and drug prior arrests, indicators for observation's decile rank for days between prior DUI offenses, and county-level police per capita, bars per capita, liquor stores per capita, unemployment, county and month fixed effects. Standard errors in parentheses.

Table 5. Robustness checks

	12 months	24 months	36 months
Panel A: Baseline	-0.137***	-0.138**	-0.117***
	(0.044)	(0.056)	(0.045)
	19,119	16,886	14,518
Panel B: Limit to those observed ≥ 36 months	-0.151***	-0.142**	-0.117***
	(0.046)	(0.058)	(0.045)
	14,518	14,518	14,518
Panel C: Limit to those on 24/7 < 2 years	-0.146***	-0.154***	-0.138***
	(0.041)	(0.056)	(0.043)
	18,737	16,584	14,320
Panel D: Include control for Convictions	-0.137***	-0.138**	-0.117**
	(0.043)	(0.058)	(0.046)
	19,119	16,886	14,518
Panel E: Include control for Time Served	-0.137***	-0.132**	-0.124***
	(0.037)	(0.053)	(0.038)
	19,119	16,886	14,518
Panel F: Exclude Probation Revocation	-0.129***	-0.122**	-0.095***
	(0.041)	(0.054)	(0.040)
	19,135	16,899	14,530
Panel G: Limited Criminal Histories	-0.134***	-0.134***	-0.109***
	(0.051)	(0.065)	(0.051)
	19,119	16,886	14,518
Panel H: Two-stage Residual Inclusion	-0.107***	-0.112**	-0.116**
	(0.045)	(0.051)	(0.056)
	19,130	16,895	14,525
Panel I: 24/7 operational at 10% DUI enrollment	-0.148***	-0.145***	-0.128***
	(0.043)	(0.054)	(0.045)
	19,119	16,886	14,518
Panel J: 24/7 operational at 40% DUI enrollment	-0.134***	-0.126**	-0.103**
	(0.044)	(0.052)	(0.040)
	19,119	16,886	14,518

* denotes statistical significance at the 10 level, ** the 5 level, and *** the 1 level. Estimated marginal effects of bivariate probit models for the effect of 24/7 on re-arrest where control variables for panels A-F and H include gender, age, categorical indicators for number of prior arrests (top-coded at 10), indicator for DUI-3 (vs. DUI-2), indicators for violent and drug prior arrests, indicators for observation's decile rank for days between prior DUI offenses, and county-level police per capita, liquor stores per capita, bars per capita, unemployment, and county and month-fixed effects. Panel G excludes categorical indicators for number of prior arrests (top-coded at 10), indicators for violent and drug prior arrests. Standard errors in parentheses; n is bottom row of each panel.

Table 6. Results by DUI level

Months since initial arrest	DUI-2 Marginal effect		N	DUI-3 Marginal effect		N
12	-.082	**	12,929	-.163	**	6,190
	(.037)			(.076)		
24	-.068		11,437	-.163	**	5,449
	(.060)			(.065)		
36	-.064		9,871	-.168	***	4,647
	(.053)			(.061)		

* denotes statistical significance at the 10 level, ** the 5 level, and *** the 1 level. Estimated marginal effects of bivariate probit models for the effect of 24/7 on re-arrest including controls for gender, age, categorical indicators for number of prior arrests (top-coded at 10), indicators for violent and drug prior arrests, indicators for observation's decile rank for days between prior DUI offenses, and county-level police per capita, liquor stores per capita, bars per capita, unemployment, and county and month-fixed effects. Standard errors in parentheses.

Table 7. Results by arrest type

Months since initial arrest	DUI			Violent Crime			Property Crime	
	Marginal effect		N	Marginal effect		N	Marginal effect	N
12	-.073	***	19,119	-.026	*	19,119	-.015	19,119
	(.107)			(.016)			(.013)	
24	-.064	**	16,886	-.019		16,886	-.009	16,886
	(.032)			(.013)			(.013)	
36	-.018		14,518	-.017		14,518	.007	14,518
	(.031)			(.014)			(.017)	

* denotes statistical significance at the 10 level, ** the 5 level, and *** the 1 level. Estimated marginal effects of bivariate probit models for the effect of 24/7 on re-arrest including controls for gender, age, categorical indicators for number of prior arrests (top-coded at 10), indicator for DUI-3 (vs. DUI-2), indicators for violent and drug prior arrests, indicators for observation's decile rank for days between prior DUI offenses, and county-level police per capita, liquor stores per capita, bars per capita, unemployment, and county and month-fixed effects. Standard errors in parentheses.

APPENDIX A. COMPARING DUI ARREST COUNTS

The data used in this analysis are drawn from the South Dakota Attorney General's Office Criminal History Database. The data provided by the AG include detailed information for all arrestees charged with driving while intoxicated (DWI) covering the period of analysis, 2004 to 2012 These data include arrest date, arresting agency, charges, incarceration time served and suspended, and final disposition for all publicly disclosed cases involving each DUI arrestee—their complete criminal history in the state of South Dakota. To verify that the data we received are a census of DUI arrests, we compare the annual count of DWI arrest events to DWI totals published by the South Dakota Department of Public Safety (DPS).[25] The data are largely similar, but not identical from year to year. The net difference may be due to expungement prior to the Attorney General's report, the timing of data recording for the DPS Report and criminal history data, or other reasons. In total, the criminal history database reports 2,568 arrests more (2.8 percent) than the DPS Report.

Fiscal Year	Criminal History Database	Department of Public Safety Report
2004	10,582	9,049
2005	11,792	10,174
2006	12,179	11,282
2007	11,284	11,756
2008	10,395	11,029
2009	9,635	10,147
2010	9,183	9,246
2011	9,416	8,744
2012	8,723	9,194

[25] 2016 Department of Public Safety South Dakota Motor Vehicle Traffic Crash Summary, as of July 1, 2017: https://dps.sd.gov/enforcement/accident_records/documents/2016factsbook.pdf

APPENDIX B. DETAILED REGRESSION OUTPUT AND MODEL DIAGNOSTICS

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Models of 1-Year Re-arrest or Probation Revocation

Variable		probit : main specification	biprobit : main specification	biprobit : ≥ 3 years follow-up	biprobit : < two years participation	biprobit : convictions only
predict: recid1						
on247		-0.33	-0.471	-0.519	-0.497	-0.47
		(0.042)	(0.151)	(0.159)	(0.142)	(0.148)
priors						
	1	(base)	(base)	(base)	(base)	(base)
	2	0.217	0.218	0.202	0.206	0.218
		(0.026)	(0.027)	(0.027)	(0.028)	(0.026)
	3	0.401	0.402	0.371	0.4	0.401
		(0.044)	(0.044)	(0.038)	(0.047)	(0.044)
	4	0.526	0.527	0.527	0.516	0.525
		(0.032)	(0.032)	(0.033)	(0.035)	(0.031)
	5	0.556	0.553	0.561	0.552	0.551
		(0.037)	(0.036)	(0.054)	(0.038)	(0.036)
	6	0.674	0.672	0.692	0.678	0.671
		(0.055)	(0.056)	(0.060)	(0.054)	(0.057)
	7	0.804	0.797	0.891	0.787	0.796
		(0.054)	(0.056)	(0.073)	(0.055)	(0.056)
	8	0.858	0.853	0.823	0.846	0.854
		(0.087)	(0.087)	(0.110)	(0.087)	(0.086)
	9	0.814	0.807	0.841	0.819	0.806
		(0.082)	(0.084)	(0.085)	(0.089)	(0.083)
	10	1.182	1.174	1.127	1.174	1.173
		(0.081)	(0.083)	(0.054)	(0.094)	(0.081)
violent prior		0.042	0.041	0.038	0.039	0.042
		(0.031)	(0.030)	(0.025)	(0.034)	(0.030)
drug prior		0.132	0.129	0.12	0.128	0.129
		(0.031)	(0.032)	(0.039)	(0.031)	(0.032)
dui3		-0.143	-0.132	-0.054	-0.121	-0.132
		(0.076)	(0.073)	(0.086)	(0.073)	(0.073)

recid1buckets					
1	0.642	0.641	0.649	0.646	0.636
	(0.072)	(0.073)	(0.058)	(0.079)	(0.070)
2	0.538	0.536	0.535	0.537	0.534
	(0.058)	(0.057)	(0.064)	(0.053)	(0.059)
3	0.419	0.42	0.429	0.42	0.418
	(0.043)	(0.044)	(0.048)	(0.047)	(0.043)
4	0.314	0.314	0.313	0.322	0.311
	(0.049)	(0.049)	(0.053)	(0.048)	(0.048)
5	0.228	0.23	0.206	0.23	0.23
	(0.067)	(0.067)	(0.082)	(0.070)	(0.068)
6	0.189	0.189	0.232	0.192	0.187
	(0.039)	(0.040)	(0.044)	(0.042)	(0.040)
7	0.212	0.212	0.248	0.216	0.212
	(0.052)	(0.052)	(0.050)	(0.056)	(0.052)
8	0.119	0.123	0.11	0.134	0.121
	(0.050)	(0.050)	(0.057)	(0.047)	(0.050)
9	0.029	0.029	0	0.038	0.029
	(0.057)	(0.056)	(0.075)	(0.059)	(0.057)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets					
1	0.652	0.647	0.601	0.646	0.642
	(0.074)	(0.075)	(0.083)	(0.072)	(0.077)
2	0.581	0.575	0.521	0.585	0.572
	(0.079)	(0.079)	(0.096)	(0.079)	(0.081)
3	0.314	0.308	0.219	0.314	0.305
	(0.083)	(0.084)	(0.087)	(0.085)	(0.085)
4	0.342	0.339	0.321	0.348	0.338
	(0.090)	(0.092)	(0.103)	(0.089)	(0.093)
5	0.409	0.41	0.356	0.418	0.407
	(0.074)	(0.074)	(0.086)	(0.076)	(0.074)
6	0.23	0.231	0.219	0.236	0.227
	(0.055)	(0.055)	(0.062)	(0.060)	(0.054)
7	0.233	0.237	0.267	0.229	0.237
	(0.065)	(0.066)	(0.070)	(0.065)	(0.066)
8	0.122	0.129	0.12	0.138	0.128
	(0.095)	(0.096)	(0.099)	(0.094)	(0.097)
9	0.017	0.025	-0.03	0.028	0.024
	(0.080)	(0.082)	(0.096)	(0.082)	(0.083)

10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	0.037	0.033	0.027	0.027	0.032
	(0.019)	(0.019)	(0.024)	(0.018)	(0.020)
age	-0.011	-0.011	-0.011	-0.011	-0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	-0.011	-0.009	-0.023	-0.011	-0.01
	(0.009)	(0.009)	(0.012)	(0.009)	(0.009)
unemployment %	-0.01	-0.009	-0.014	-0.008	-0.009
	(0.025)	(0.025)	(0.027)	(0.025)	(0.025)
predict: on247					
thresh25		0.903	0.846	0.898	0.907
		(0.118)	(0.129)	(0.114)	(0.120)
thresh10					
thresh40					
priors					
1		(base)	(base)	(base)	(base)
2		0.032	0.056	0.019	0.035
		(0.027)	(0.033)	(0.025)	(0.027)
3		0.036	0.039	0.019	0.039
		(0.029)	(0.031)	(0.037)	(0.030)
4		0.029	0.104	0.018	0.034
		(0.032)	(0.044)	(0.035)	(0.033)
5		-0.057	-0.01	-0.074	-0.05
		(0.035)	(0.045)	(0.037)	(0.035)
6		-0.019	0.019	-0.037	-0.013
		(0.043)	(0.053)	(0.043)	(0.041)
7		-0.131	-0.067	-0.126	-0.127
		(0.061)	(0.094)	(0.061)	(0.060)
8		-0.139	-0.058	-0.16	-0.141
		(0.072)	(0.093)	(0.068)	(0.074)
9		-0.166	-0.105	-0.194	-0.152
		(0.070)	(0.067)	(0.075)	(0.068)
10		-0.19	-0.095	-0.189	-0.183

	(0.049)	(0.075)	(0.051)	(0.050)
violent prior	-0.018	-0.02	-0.015	-0.019
	(0.028)	(0.031)	(0.028)	(0.027)
drug prior	-0.079	-0.038	-0.082	-0.08
	(0.029)	(0.038)	(0.030)	(0.028)
dui3	0.35	0.406	0.325	0.348
	(0.083)	(0.095)	(0.084)	(0.085)
recid1buckets				
1	0.044	0.133	0.043	0.064
	(0.111)	(0.124)	(0.115)	(0.112)
2	0.011	0.139	0.012	0.02
	(0.091)	(0.115)	(0.090)	(0.091)
3	0.092	0.178	0.081	0.1
	(0.093)	(0.117)	(0.102)	(0.094)
4	0.058	0.204	0.073	0.067
	(0.076)	(0.086)	(0.078)	(0.077)
5	0.067	0.192	0.052	0.064
	(0.076)	(0.087)	(0.078)	(0.074)
6	0.039	0.125	0.037	0.043
	(0.058)	(0.083)	(0.064)	(0.058)
7	0.045	0.103	0.017	0.047
	(0.058)	(0.061)	(0.067)	(0.058)
8	0.124	0.13	0.116	0.131
	(0.058)	(0.062)	(0.062)	(0.055)
9	0.043	0.035	0.044	0.04
	(0.043)	(0.046)	(0.044)	(0.044)
10	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets				
1	-0.133	-0.068	-0.104	-0.113
	(0.102)	(0.110)	(0.105)	(0.103)
2	-0.101	0.034	-0.094	-0.086
	(0.095)	(0.090)	(0.085)	(0.098)
3	-0.154	-0.035	-0.141	-0.141
	(0.090)	(0.083)	(0.093)	(0.090)
4	-0.096	0.069	-0.086	-0.09
	(0.119)	(0.173)	(0.123)	(0.120)
5	0.02	0.27	0.038	0.031

		(0.117)	(0.127)	(0.120)	(0.114)
6		0.004	0.278	0.009	0.016
		(0.069)	(0.080)	(0.070)	(0.071)
7		0.094	0.36	0.084	0.095
		(0.096)	(0.110)	(0.093)	(0.093)
8		0.184	0.176	0.182	0.191
		(0.069)	(0.068)	(0.072)	(0.069)
9		0.18	0.142	0.176	0.183
		(0.078)	(0.076)	(0.091)	(0.078)
10		(omitted)	(omitted)	(omitted)	(omitted)
male		-0.099	-0.092	-0.102	-0.093
		(0.042)	(0.046)	(0.042)	(0.043)
age		-0.001	-0.002	-0.001	0
		(0.001)	(0.001)	(0.001)	(0.001)
police per capita		0.03	0.064	0.034	0.032
		(0.020)	(0.038)	(0.023)	(0.019)
unemployment %		0.027	-0.061	0.02	0.028
		(0.038)	(0.049)	(0.037)	(0.037)
Statistics					
N	19114	19119	14518	18737	19119
ρ		0.088	0.13	0.11	0.09

Variable	biprobit control for time served	biprobit : exclude probation violations	biprobit limited crim history	biprobit 10% threshold	biprobit 40% threshold
predict: recid1					
on247	-0.474	-0.445	-0.436	-0.508	-0.457
	(0.128)	(0.143)	(0.169)	(0.148)	(0.153)
priors					
1	(base)	-0.194		(base)	(base)
		(0.283)			
2	0.202	0.021		0.218	0.218
	(0.026)	(0.289)		(0.027)	(0.026)
3	0.378	0.208		0.402	0.402
	(0.049)	(0.285)		(0.044)	(0.044)

4	0.503	0.336		0.527	0.527
	(0.036)	(0.285)		(0.032)	(0.032)
5	0.515	0.365		0.552	0.553
	(0.037)	(0.294)		(0.037)	(0.036)
6	0.637	0.477		0.671	0.672
	(0.052)	(0.294)		(0.056)	(0.056)
7	0.752	0.61		0.795	0.798
	(0.053)	(0.289)		(0.056)	(0.056)
8	0.816	0.666		0.851	0.854
	(0.091)	(0.296)		(0.088)	(0.087)
9	0.782	0.622		0.805	0.808
	(0.090)	(0.313)		(0.084)	(0.084)
10	1.133	0.989		1.171	1.175
	(0.092)	(0.286)		(0.083)	(0.083)
violent prior	0.043	0.041		0.041	0.042
	(0.031)	(0.031)		(0.030)	(0.030)
drug prior	0.144	0.123		0.128	0.129
	(0.032)	(0.032)		(0.032)	(0.032)
dui3	-0.152	-0.135	0.098	-0.129	-0.133
	(0.074)	(0.074)	(0.070)	(0.073)	(0.073)
recid1buckets					
1	0.624	0.634	0.479	0.64	0.641
	(0.078)	(0.077)	(0.076)	(0.074)	(0.073)
2	0.494	0.527	0.368	0.535	0.536
	(0.050)	(0.054)	(0.056)	(0.057)	(0.058)
3	0.376	0.415	0.275	0.42	0.42
	(0.049)	(0.046)	(0.043)	(0.044)	(0.044)
4	0.274	0.306	0.174	0.314	0.314
	(0.051)	(0.050)	(0.048)	(0.049)	(0.049)
5	0.193	0.217	0.111	0.23	0.23
	(0.075)	(0.068)	(0.067)	(0.068)	(0.067)
6	0.16	0.179	0.107	0.189	0.189
	(0.042)	(0.043)	(0.036)	(0.040)	(0.040)
7	0.184	0.209	0.128	0.212	0.212
	(0.056)	(0.052)	(0.061)	(0.053)	(0.052)
8	0.089	0.113	0.069	0.124	0.122
	(0.047)	(0.049)	(0.045)	(0.050)	(0.050)
9	0.009	0.015	-0.014	0.029	0.029
	(0.058)	(0.060)	(0.054)	(0.056)	(0.056)

10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets					
1	0.617	0.636	0.514	0.645	0.647
	(0.068)	(0.071)	(0.066)	(0.075)	(0.075)
2	0.563	0.568	0.461	0.573	0.576
	(0.068)	(0.082)	(0.066)	(0.079)	(0.079)
3	0.284	0.291	0.225	0.306	0.309
	(0.082)	(0.087)	(0.078)	(0.084)	(0.084)
4	0.289	0.341	0.255	0.338	0.339
	(0.083)	(0.087)	(0.081)	(0.093)	(0.092)
5	0.381	0.417	0.34	0.41	0.41
	(0.071)	(0.072)	(0.069)	(0.074)	(0.074)
6	0.226	0.206	0.171	0.23	0.231
	(0.060)	(0.053)	(0.053)	(0.054)	(0.055)
7	0.216	0.214	0.164	0.238	0.237
	(0.065)	(0.065)	(0.064)	(0.067)	(0.066)
8	0.123	0.13	0.085	0.131	0.129
	(0.094)	(0.093)	(0.085)	(0.097)	(0.096)
9	0.003	0.008	0.008	0.026	0.024
	(0.085)	(0.081)	(0.091)	(0.081)	(0.082)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	0.037	0.036	0.086	0.032	0.033
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
age	-0.011	-0.011	-0.013	-0.011	-0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	-0.004	-0.01	-0.007	-0.009	-0.01
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
unemployment %	-0.008	-0.012	-0.009	-0.009	-0.009
	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)
predict: on247					
thresh25	0.935	0.903	0.898		
	(0.122)	(0.119)	(0.118)		
thresh10				0.9	
				(0.130)	
thresh40					0.909

						(0.092)
priors						
	1	(base)	0.503		(base)	(base)
			(0.348)			
	2	0.017	0.535		0.028	0.033
		(0.027)	(0.350)		(0.027)	(0.028)
	3	0.008	0.54		0.036	0.039
		(0.026)	(0.348)		(0.029)	(0.030)
	4	-0.001	0.534		0.027	0.033
		(0.029)	(0.348)		(0.032)	(0.031)
	5	-0.105	0.447		-0.059	-0.053
		(0.033)	(0.346)		(0.036)	(0.034)
	6	-0.068	0.485		-0.02	-0.013
		(0.045)	(0.356)		(0.042)	(0.043)
	7	-0.196	0.372		-0.126	-0.125
		(0.064)	(0.359)		(0.062)	(0.061)
	8	-0.195	0.364		-0.142	-0.136
		(0.076)	(0.363)		(0.072)	(0.072)
	9	-0.212	0.338		-0.168	-0.161
		(0.071)	(0.342)		(0.070)	(0.070)
	10	-0.263	0.314		-0.189	-0.175
		(0.047)	(0.354)		(0.049)	(0.048)
violent prior		-0.018	-0.018		-0.016	-0.024
		(0.030)	(0.028)		(0.027)	(0.028)
drug prior		-0.063	-0.079		-0.076	-0.081
		(0.030)	(0.029)		(0.029)	(0.028)
dui3		0.338	0.342	0.34	0.348	0.349
		(0.088)	(0.082)	(0.088)	(0.082)	(0.084)
recid1buckets						
	1	0.016	0.036	0.062	0.043	0.044
		(0.114)	(0.109)	(0.111)	(0.111)	(0.111)
	2	-0.048	0.02	0.032	0.007	0.009
		(0.093)	(0.090)	(0.090)	(0.091)	(0.092)
	3	0.028	0.083	0.109	0.09	0.094
		(0.087)	(0.092)	(0.092)	(0.093)	(0.093)
	4	0.001	0.06	0.074	0.058	0.062
		(0.076)	(0.075)	(0.076)	(0.076)	(0.076)
	5	0.011	0.066	0.087	0.065	0.067

	(0.071)	(0.082)	(0.076)	(0.076)	(0.077)
6	-0.009	0.034	0.05	0.039	0.042
	(0.055)	(0.055)	(0.059)	(0.058)	(0.058)
7	0.002	0.045	0.06	0.042	0.045
	(0.056)	(0.058)	(0.058)	(0.059)	(0.058)
8	0.077	0.122	0.134	0.121	0.129
	(0.054)	(0.058)	(0.056)	(0.058)	(0.057)
9	0.014	0.038	0.05	0.041	0.044
	(0.044)	(0.041)	(0.043)	(0.043)	(0.045)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets					
1	-0.191	-0.135	-0.115	-0.13	-0.134
	(0.101)	(0.102)	(0.098)	(0.102)	(0.100)
2	-0.123	-0.091	-0.088	-0.102	-0.105
	(0.086)	(0.091)	(0.099)	(0.095)	(0.095)
3	-0.189	-0.169	-0.146	-0.15	-0.158
	(0.093)	(0.094)	(0.085)	(0.090)	(0.090)
4	-0.159	-0.073	-0.086	-0.099	-0.09
	(0.121)	(0.119)	(0.117)	(0.120)	(0.120)
5	-0.021	0.032	0.027	0.024	0.024
	(0.120)	(0.116)	(0.113)	(0.118)	(0.115)
6	0.009	0.019	0.013	0.012	0.005
	(0.073)	(0.070)	(0.067)	(0.070)	(0.069)
7	0.079	0.104	0.102	0.089	0.091
	(0.099)	(0.099)	(0.095)	(0.097)	(0.096)
8	0.19	0.177	0.182	0.185	0.184
	(0.075)	(0.069)	(0.070)	(0.070)	(0.069)
9	0.174	0.198	0.181	0.182	0.189
	(0.077)	(0.075)	(0.077)	(0.079)	(0.077)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	-0.093	-0.099	-0.108	-0.1	-0.099
	(0.036)	(0.042)	(0.042)	(0.042)	(0.042)
age	0	-0.001	0	0	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	0.038	0.03	0.03	0.029	0.029
	(0.022)	(0.020)	(0.020)	(0.020)	(0.019)

unemployment %	0.032	0.029	0.028	0.039	0.027
	(0.041)	(0.038)	(0.038)	(0.038)	(0.038)
Statistics					
N	19119	19135	19119	19119	19119
ρ	0.059	0.065	0.059	0.111	0.08

Models of 2-year Re-arrest or Probation Revocation

	probit : main specification	biprobit : main specification	biprobit : ≥ 3 years follow-up	biprobit : < two years participation	biprobit : convictions only
predict: recid2					
on247	-0.233	-0.407	-0.421	-0.455	-0.408
	(0.029)	(0.167)	(0.176)	(0.168)	(0.175)
priors					
1	(base)	(base)	(base)	(base)	(base)
2	0.228	0.229	0.255	0.221	0.229
	(0.025)	(0.025)	(0.029)	(0.025)	(0.025)
3	0.43	0.432	0.443	0.434	0.432
	(0.032)	(0.031)	(0.030)	(0.030)	(0.031)
4	0.644	0.646	0.677	0.637	0.646
	(0.039)	(0.039)	(0.043)	(0.039)	(0.039)
5	0.665	0.661	0.676	0.659	0.661
	(0.065)	(0.064)	(0.067)	(0.068)	(0.063)
6	0.82	0.818	0.852	0.824	0.818
	(0.042)	(0.041)	(0.048)	(0.044)	(0.041)
7	1.032	1.025	1.111	1.016	1.025
	(0.059)	(0.061)	(0.082)	(0.061)	(0.062)
8	0.947	0.942	0.966	0.923	0.941
	(0.073)	(0.072)	(0.082)	(0.074)	(0.072)
9	1.014	1.006	1.053	1.019	1.007
	(0.076)	(0.076)	(0.076)	(0.078)	(0.076)
10	1.35	1.341	1.354	1.351	1.342
	(0.053)	(0.056)	(0.046)	(0.059)	(0.056)
violent prior	0.036	0.035	0.028	0.03	0.035
	(0.025)	(0.025)	(0.024)	(0.026)	(0.025)
drug prior	0.103	0.1	0.071	0.097	0.099
	(0.040)	(0.040)	(0.042)	(0.039)	(0.040)
dui3	-0.138	-0.124	-0.145	-0.12	-0.124
	(0.074)	(0.065)	(0.073)	(0.067)	(0.064)
recid1buckets					
1	0.642	0.641	0.634	0.648	0.642

	(0.052)	(0.052)	(0.056)	(0.053)	(0.051)
2	0.554	0.552	0.549	0.556	0.553
	(0.063)	(0.062)	(0.063)	(0.060)	(0.062)
3	0.42	0.421	0.414	0.425	0.422
	(0.050)	(0.048)	(0.055)	(0.047)	(0.048)
4	0.325	0.326	0.294	0.333	0.326
	(0.054)	(0.053)	(0.058)	(0.054)	(0.052)
5	0.323	0.325	0.288	0.332	0.325
	(0.071)	(0.071)	(0.078)	(0.076)	(0.071)
6	0.226	0.226	0.233	0.234	0.226
	(0.036)	(0.036)	(0.041)	(0.036)	(0.036)
7	0.272	0.274	0.273	0.286	0.274
	(0.043)	(0.042)	(0.044)	(0.043)	(0.042)
8	0.116	0.118	0.106	0.13	0.119
	(0.055)	(0.053)	(0.051)	(0.051)	(0.053)
9	0.056	0.056	0.005	0.069	0.055
	(0.066)	(0.065)	(0.075)	(0.064)	(0.065)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets					
1	0.624	0.618	0.608	0.624	0.619
	(0.073)	(0.073)	(0.072)	(0.068)	(0.075)
2	0.615	0.609	0.642	0.626	0.61
	(0.111)	(0.112)	(0.102)	(0.101)	(0.113)
3	0.344	0.339	0.361	0.353	0.339
	(0.077)	(0.077)	(0.076)	(0.072)	(0.078)
4	0.336	0.333	0.384	0.357	0.334
	(0.106)	(0.108)	(0.108)	(0.103)	(0.108)
5	0.374	0.378	0.392	0.391	0.378
	(0.063)	(0.064)	(0.061)	(0.061)	(0.065)
6	0.216	0.223	0.225	0.246	0.224
	(0.048)	(0.050)	(0.056)	(0.058)	(0.050)
7	0.251	0.262	0.293	0.282	0.262
	(0.091)	(0.097)	(0.083)	(0.093)	(0.097)
8	0.131	0.14	0.175	0.145	0.14
	(0.092)	(0.095)	(0.092)	(0.086)	(0.096)
9	0.064	0.07	0.039	0.084	0.071
	(0.066)	(0.070)	(0.077)	(0.070)	(0.070)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)

male	0.033	0.028	0.031	0.023	0.028
	(0.019)	(0.017)	(0.021)	(0.017)	(0.017)
age	-0.014	-0.014	-0.013	-0.013	-0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	-0.003	-0.001	0.005	-0.002	-0.001
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)
unemployment %	-0.011	-0.011	-0.028	-0.009	-0.011
	(0.022)	(0.022)	(0.026)	(0.022)	(0.022)
predict: on247					
thresh25		0.891	0.846	0.887	0.895
		(0.129)	(0.129)	(0.126)	(0.131)
thresh10					
thresh40					
priors					
1		(base)	(base)	(base)	(base)
2		0.033	0.054	0.017	0.035
		(0.029)	(0.034)	(0.028)	(0.029)
3		0.065	0.035	0.039	0.067
		(0.035)	(0.032)	(0.043)	(0.037)
4		0.048	0.1	0.026	0.052
		(0.037)	(0.043)	(0.038)	(0.037)
5		-0.048	-0.012	-0.073	-0.045
		(0.037)	(0.045)	(0.037)	(0.037)
6		0.004	0.013	-0.017	0.011
		(0.046)	(0.058)	(0.046)	(0.046)
7		-0.097	-0.071	-0.093	-0.098
		(0.075)	(0.094)	(0.075)	(0.077)
8		-0.091	-0.059	-0.131	-0.097
		(0.070)	(0.092)	(0.063)	(0.070)
9		-0.153	-0.106	-0.212	-0.134
		(0.092)	(0.067)	(0.095)	(0.088)
10		-0.14	-0.1	-0.146	-0.134
		(0.052)	(0.073)	(0.054)	(0.053)

violent prior	-0.008	-0.02	-0.001	-0.007
	(0.026)	(0.032)	(0.028)	(0.025)
drug prior	-0.061	-0.034	-0.061	-0.063
	(0.028)	(0.038)	(0.030)	(0.029)
dui3	0.381	0.409	0.362	0.376
	(0.093)	(0.097)	(0.096)	(0.097)
recid1buckets				
1	0.065	0.134	0.064	0.091
	(0.112)	(0.122)	(0.114)	(0.113)
2	0.044	0.139	0.044	0.056
	(0.098)	(0.114)	(0.096)	(0.098)
3	0.107	0.178	0.105	0.117
	(0.104)	(0.117)	(0.108)	(0.105)
4	0.085	0.202	0.096	0.098
	(0.075)	(0.084)	(0.076)	(0.075)
5	0.088	0.194	0.066	0.084
	(0.073)	(0.087)	(0.074)	(0.072)
6	0.065	0.126	0.061	0.073
	(0.059)	(0.082)	(0.065)	(0.059)
7	0.082	0.102	0.054	0.082
	(0.058)	(0.061)	(0.067)	(0.057)
8	0.109	0.132	0.097	0.116
	(0.057)	(0.061)	(0.061)	(0.054)
9	0.03	0.037	0.032	0.028
	(0.049)	(0.047)	(0.050)	(0.050)
10	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets				
1	-0.108	-0.066	-0.077	-0.079
	(0.103)	(0.110)	(0.104)	(0.102)
2	-0.069	0.035	-0.054	-0.05
	(0.089)	(0.091)	(0.086)	(0.091)
3	-0.11	-0.038	-0.103	-0.093
	(0.085)	(0.082)	(0.082)	(0.084)
4	-0.051	0.071	-0.042	-0.041
	(0.129)	(0.174)	(0.132)	(0.129)
5	0.081	0.268	0.089	0.099
	(0.116)	(0.126)	(0.117)	(0.111)
6	0.132	0.278	0.146	0.146

		(0.067)	(0.080)	(0.069)	(0.067)
7		0.241	0.359	0.224	0.243
		(0.096)	(0.107)	(0.094)	(0.093)
8		0.19	0.174	0.184	0.204
		(0.060)	(0.067)	(0.064)	(0.059)
9		0.143	0.142	0.143	0.15
		(0.076)	(0.076)	(0.088)	(0.078)
10		(omitted)	(omitted)	(omitted)	(omitted)
male		-0.11	-0.092	-0.115	-0.104
		(0.046)	(0.045)	(0.047)	(0.048)
age		-0.002	-0.002	-0.002	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)
police per capita		0.041	0.064	0.038	0.044
		(0.029)	(0.038)	(0.030)	(0.029)
unemployment %		0.011	-0.061	0.008	0.011
		(0.041)	(0.049)	(0.040)	(0.040)
Statistics					
N	16882	16886	14518	16584	16886
ρ		0.108	0.129	0.14	0.109

	biprobit control for time served	biprobit : exclude probation violations	biprobit limited crim history	biprobit 10% threshold	biprobit 40% threshold
predict: recid2					
on247	-0.393	-0.362	-0.373	-0.43	-0.373
	(0.160)	(0.161)	(0.184)	(0.162)	(0.156)
priors					
1	(base)	0.417		(base)	(base)
		(0.340)			
2	0.214	0.644		0.229	0.229
	(0.025)	(0.346)		(0.025)	(0.025)
3	0.408	0.849		0.432	0.431
	(0.036)	(0.341)		(0.031)	(0.031)
4	0.624	1.066		0.646	0.646
	(0.039)	(0.335)		(0.039)	(0.039)

5	0.626	1.082		0.66	0.662
	(0.069)	(0.347)		(0.064)	(0.064)
6	0.787	1.23		0.817	0.818
	(0.039)	(0.340)		(0.041)	(0.042)
7	0.99	1.454		1.024	1.026
	(0.060)	(0.332)		(0.062)	(0.061)
8	0.905	1.371		0.941	0.943
	(0.073)	(0.355)		(0.072)	(0.072)
9	0.987	1.436		1.005	1.008
	(0.079)	(0.357)		(0.076)	(0.076)
10	1.307	1.773		1.34	1.344
	(0.061)	(0.332)		(0.056)	(0.055)
violent prior	0.038	0.029		0.035	0.035
	(0.026)	(0.024)		(0.025)	(0.025)
drug prior	0.113	0.097		0.099	0.1
	(0.039)	(0.040)		(0.040)	(0.040)
dui3	-0.141	-0.121	0.144	-0.122	-0.127
	(0.068)	(0.067)	(0.065)	(0.064)	(0.067)
recid1buckets					
1	0.627	0.629	0.466	0.64	0.641
	(0.053)	(0.055)	(0.049)	(0.052)	(0.052)
2	0.514	0.543	0.378	0.552	0.553
	(0.055)	(0.061)	(0.058)	(0.061)	(0.062)
3	0.383	0.414	0.267	0.421	0.421
	(0.048)	(0.050)	(0.045)	(0.048)	(0.048)
4	0.29	0.318	0.18	0.326	0.326
	(0.056)	(0.057)	(0.051)	(0.053)	(0.053)
5	0.294	0.314	0.199	0.326	0.325
	(0.077)	(0.066)	(0.070)	(0.071)	(0.071)
6	0.199	0.227	0.133	0.226	0.226
	(0.037)	(0.037)	(0.035)	(0.036)	(0.036)
7	0.248	0.264	0.184	0.274	0.274
	(0.045)	(0.041)	(0.050)	(0.042)	(0.042)
8	0.088	0.111	0.061	0.119	0.118
	(0.051)	(0.052)	(0.051)	(0.053)	(0.054)
9	0.033	0.041	0.014	0.055	0.056
	(0.066)	(0.063)	(0.059)	(0.065)	(0.065)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)

recid2buckets					
1	0.596	0.608	0.47	0.617	0.62
	(0.066)	(0.071)	(0.062)	(0.073)	(0.073)
2	0.597	0.587	0.479	0.608	0.61
	(0.096)	(0.110)	(0.094)	(0.112)	(0.112)
3	0.322	0.313	0.246	0.338	0.34
	(0.070)	(0.083)	(0.070)	(0.077)	(0.077)
4	0.298	0.299	0.247	0.333	0.334
	(0.099)	(0.113)	(0.097)	(0.108)	(0.108)
5	0.355	0.377	0.31	0.378	0.377
	(0.059)	(0.067)	(0.060)	(0.064)	(0.064)
6	0.224	0.188	0.167	0.224	0.222
	(0.050)	(0.049)	(0.050)	(0.050)	(0.050)
7	0.237	0.232	0.179	0.263	0.26
	(0.088)	(0.084)	(0.089)	(0.098)	(0.096)
8	0.135	0.11	0.095	0.141	0.138
	(0.093)	(0.103)	(0.088)	(0.095)	(0.094)
9	0.055	0.038	0.044	0.071	0.069
	(0.070)	(0.071)	(0.077)	(0.070)	(0.070)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	0.034	0.031	0.086	0.027	0.029
	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)
age	-0.013	-0.014	-0.016	-0.014	-0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	0.002	-0.002	0.002	-0.001	-0.002
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
unemployment %	-0.01	-0.015	-0.01	-0.01	-0.011
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
predict: on247					
thresh25	0.928	0.891	0.887		
	(0.132)	(0.129)	(0.130)		
thresh10				0.88	
				(0.135)	
thresh40					0.893
					(0.101)

priors						
	1	(base)	1.008		(base)	(base)
			(0.642)			
	2	0.014	1.042		0.03	0.034
		(0.028)	(0.648)		(0.029)	(0.029)
	3	0.032	1.073		0.064	0.069
		(0.031)	(0.639)		(0.035)	(0.036)
	4	0.014	1.057		0.045	0.053
		(0.035)	(0.646)		(0.038)	(0.036)
	5	-0.105	0.96		-0.049	-0.044
		(0.036)	(0.648)		(0.037)	(0.037)
	6	-0.048	1.014		0.003	0.012
		(0.046)	(0.650)		(0.045)	(0.045)
	7	-0.16	0.911		-0.091	-0.091
		(0.082)	(0.658)		(0.075)	(0.074)
	8	-0.155	0.916		-0.093	-0.088
		(0.069)	(0.661)		(0.068)	(0.070)
	9	-0.207	0.856		-0.155	-0.145
		(0.088)	(0.634)		(0.092)	(0.092)
	10	-0.218	0.869		-0.139	-0.122
		(0.051)	(0.643)		(0.052)	(0.051)
violent prior		-0.005	-0.008		-0.007	-0.016
		(0.028)	(0.027)		(0.026)	(0.027)
drug prior		-0.043	-0.061		-0.057	-0.065
		(0.030)	(0.028)		(0.028)	(0.028)
dui3		0.369	0.373	0.382	0.377	0.38
		(0.096)	(0.093)	(0.098)	(0.092)	(0.094)
recid1buckets						
	1	0.039	0.059	0.078	0.063	0.066
		(0.115)	(0.111)	(0.111)	(0.113)	(0.113)
	2	-0.017	0.057	0.059	0.041	0.044
		(0.101)	(0.097)	(0.096)	(0.098)	(0.099)
	3	0.047	0.103	0.119	0.103	0.109
		(0.099)	(0.105)	(0.103)	(0.105)	(0.104)
	4	0.028	0.09	0.097	0.085	0.091
		(0.076)	(0.073)	(0.075)	(0.075)	(0.076)
	5	0.033	0.089	0.102	0.085	0.086
		(0.069)	(0.078)	(0.074)	(0.073)	(0.075)
	6	0.015	0.065	0.076	0.065	0.069

	(0.058)	(0.058)	(0.059)	(0.059)	(0.060)
7	0.031	0.084	0.095	0.078	0.083
	(0.055)	(0.057)	(0.057)	(0.059)	(0.058)
8	0.06	0.11	0.116	0.106	0.116
	(0.053)	(0.057)	(0.056)	(0.058)	(0.058)
9	-0.006	0.031	0.036	0.028	0.033
	(0.048)	(0.048)	(0.047)	(0.049)	(0.050)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets					
1	-0.158	-0.113	-0.095	-0.103	-0.11
	(0.102)	(0.104)	(0.099)	(0.103)	(0.100)
2	-0.093	-0.054	-0.061	-0.07	-0.073
	(0.084)	(0.086)	(0.090)	(0.089)	(0.089)
3	-0.137	-0.122	-0.104	-0.103	-0.115
	(0.087)	(0.089)	(0.080)	(0.085)	(0.084)
4	-0.11	-0.027	-0.045	-0.051	-0.044
	(0.136)	(0.126)	(0.127)	(0.131)	(0.129)
5	0.042	0.097	0.084	0.086	0.083
	(0.117)	(0.117)	(0.113)	(0.117)	(0.114)
6	0.144	0.149	0.136	0.138	0.133
	(0.071)	(0.065)	(0.066)	(0.067)	(0.066)
7	0.219	0.254	0.246	0.234	0.236
	(0.096)	(0.098)	(0.094)	(0.095)	(0.097)
8	0.2	0.182	0.186	0.191	0.189
	(0.062)	(0.059)	(0.060)	(0.061)	(0.061)
9	0.138	0.166	0.144	0.146	0.155
	(0.075)	(0.073)	(0.078)	(0.078)	(0.076)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	-0.102	-0.11	-0.117	-0.112	-0.11
	(0.040)	(0.046)	(0.046)	(0.046)	(0.046)
age	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	0.045	0.041	0.041	0.044	0.037
	(0.030)	(0.029)	(0.029)	(0.030)	(0.026)
unemployment %	0.013	0.012	0.012	0.022	0.012

	(0.044)	(0.041)	(0.041)	(0.039)	(0.041)
Statistics					
N	16886	16899	16886	16886	16886
ρ	0.073	0.076	0.083	0.123	0.087

Models of 3-year Re-arrest or Probation Revocation

		probit : main specification	biprobit 80: ≥ 3 years follow-up	biprobit 60: ≥ 3 years follow-up	biprobit3_720: ≥ 3 years follow-up	biprobit : main specification
predict: recid3						
on247		-0.189				-0.334
		(0.034)				(0.130)
priors						
	1	(base)				(base)
	2	0.265				0.266
		(0.037)				(0.037)
	3	0.446				0.447
		(0.030)				(0.030)
	4	0.671				0.674
		(0.042)				(0.042)
	5	0.717				0.716
		(0.068)				(0.068)
	6	0.855				0.854
		(0.065)				(0.064)
	7	1.122				1.118
		(0.069)				(0.067)
	8	1.04				1.037
		(0.065)				(0.066)
	9	1.155				1.15
		(0.065)				(0.066)
	10	1.433				1.429
		(0.035)				(0.037)
violent prior		0.037				0.036
		(0.024)				(0.024)
drug prior		0.091				0.089
		(0.047)				(0.047)
dui3		-0.142				-0.131
		(0.062)				(0.061)
recid1buckets						

1	0.64	0.641
	(0.050)	(0.051)
2	0.571	0.572
	(0.069)	(0.068)
3	0.443	0.446
	(0.053)	(0.052)
4	0.272	0.276
	(0.054)	(0.055)
5	0.247	0.251
	(0.050)	(0.050)
6	0.268	0.269
	(0.048)	(0.050)
7	0.257	0.258
	(0.047)	(0.047)
8	0.129	0.132
	(0.049)	(0.049)
9	0.021	0.021
	(0.058)	(0.058)
10	(omitted)	(omitted)
recid2buckets		
1	0.589	0.587
	(0.070)	(0.070)
2	0.648	0.647
	(0.064)	(0.064)
3	0.415	0.413
	(0.067)	(0.068)
4	0.374	0.377
	(0.094)	(0.095)
5	0.408	0.418
	(0.065)	(0.064)
6	0.154	0.165
	(0.053)	(0.055)
7	0.233	0.246
	(0.080)	(0.081)
8	0.15	0.156
	(0.059)	(0.062)
9	0.079	0.083
	(0.074)	(0.075)
10	(omitted)	(omitted)

male	0.021				0.018
	(0.020)				(0.019)
age	-0.015				-0.015
	(0.001)				(0.001)
police per capita	0.004				0.004
	(0.011)				(0.011)
unemployment %	-0.042				-0.043
	(0.025)				(0.024)
predict: on247					
thresh25		0.844	0.846	0.846	0.847
		(0.130)	(0.129)	(0.129)	(0.129)
thresh10					
thresh40					
priors					
1		(base)	(base)	(base)	(base)
2		0.056	0.056	0.054	0.055
		(0.033)	(0.033)	(0.034)	(0.033)
3		0.039	0.039	0.035	0.037
		(0.031)	(0.031)	(0.032)	(0.031)
4		0.104	0.104	0.1	0.102
		(0.044)	(0.044)	(0.043)	(0.043)
5		-0.007	-0.01	-0.012	-0.011
		(0.044)	(0.045)	(0.045)	(0.046)
6		0.022	0.019	0.013	0.017
		(0.052)	(0.053)	(0.058)	(0.054)
7		-0.066	-0.067	-0.071	-0.07
		(0.093)	(0.094)	(0.094)	(0.095)
8		-0.056	-0.058	-0.059	-0.061
		(0.092)	(0.093)	(0.092)	(0.090)
9		-0.1	-0.105	-0.106	-0.103
		(0.069)	(0.067)	(0.067)	(0.067)
10		-0.096	-0.095	-0.1	-0.099
		(0.075)	(0.075)	(0.073)	(0.073)

violent prior	-0.022	-0.02	-0.02	-0.02
	(0.030)	(0.031)	(0.032)	(0.031)
drug prior	-0.038	-0.038	-0.034	-0.036
	(0.038)	(0.038)	(0.038)	(0.038)
dui3	0.405	0.406	0.409	0.408
	(0.096)	(0.095)	(0.097)	(0.096)
recid1buckets				
1	0.136	0.133	0.134	0.137
	(0.125)	(0.124)	(0.122)	(0.124)
2	0.143	0.139	0.139	0.142
	(0.117)	(0.115)	(0.114)	(0.117)
3	0.178	0.178	0.178	0.177
	(0.116)	(0.117)	(0.117)	(0.116)
4	0.204	0.204	0.202	0.202
	(0.086)	(0.086)	(0.084)	(0.086)
5	0.194	0.192	0.194	0.193
	(0.088)	(0.087)	(0.087)	(0.087)
6	0.125	0.125	0.126	0.126
	(0.084)	(0.083)	(0.082)	(0.083)
7	0.108	0.103	0.102	0.105
	(0.062)	(0.061)	(0.061)	(0.062)
8	0.132	0.13	0.132	0.134
	(0.061)	(0.062)	(0.061)	(0.060)
9	0.035	0.035	0.037	0.039
	(0.046)	(0.046)	(0.047)	(0.048)
10	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets				
1	-0.067	-0.068	-0.066	-0.066
	(0.112)	(0.110)	(0.110)	(0.111)
2	0.033	0.034	0.035	0.031
	(0.091)	(0.090)	(0.091)	(0.090)
3	-0.036	-0.035	-0.038	-0.039
	(0.085)	(0.083)	(0.082)	(0.083)
4	0.07	0.069	0.071	0.07
	(0.175)	(0.173)	(0.174)	(0.174)
5	0.269	0.27	0.268	0.267
	(0.127)	(0.127)	(0.126)	(0.126)

6		0.28	0.278	0.278	0.279
		(0.079)	(0.080)	(0.080)	(0.079)
7		0.362	0.36	0.359	0.357
		(0.111)	(0.110)	(0.107)	(0.108)
8		0.178	0.176	0.174	0.173
		(0.069)	(0.068)	(0.067)	(0.069)
9		0.147	0.142	0.142	0.146
		(0.075)	(0.076)	(0.076)	(0.074)
10		(omitted)	(omitted)	(omitted)	(omitted)
male		-0.093	-0.092	-0.092	-0.092
		(0.046)	(0.046)	(0.045)	(0.046)
age		-0.002	-0.002	-0.002	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)
police per capita		0.064	0.064	0.064	0.064
		(0.038)	(0.038)	(0.038)	(0.038)
unemployment %		-0.06	-0.061	-0.061	-0.06
		(0.049)	(0.049)	(0.049)	(0.049)
Statistics					
N	14513	14518	14518	14518	14518
ρ		0.082	0.13	0.129	0.09

	biprobit : ≥ 3 years follow-up	biprobit : < two years participation	biprobit : convictions only	biprobit control for time served	biprobit : exclude probation violations
predict: recid3					
on247	-0.334	-0.393	-0.334	-0.357	-0.272
	(0.130)	(0.124)	(0.131)	(0.109)	(0.115)
priors					
1	(base)	(base)	(base)	(base)	0.229
					(0.328)
2	0.266	0.259	0.266	0.253	0.491
	(0.037)	(0.036)	(0.037)	(0.036)	(0.338)
3	0.447	0.447	0.447	0.424	0.677
	(0.030)	(0.029)	(0.030)	(0.033)	(0.325)
4	0.674	0.663	0.675	0.651	0.904

	(0.042)	(0.042)	(0.042)	(0.038)	(0.339)
5	0.716	0.708	0.717	0.681	0.951
	(0.068)	(0.069)	(0.067)	(0.074)	(0.317)
6	0.854	0.854	0.855	0.824	1.079
	(0.064)	(0.062)	(0.063)	(0.061)	(0.336)
7	1.118	1.1	1.119	1.083	1.356
	(0.067)	(0.065)	(0.068)	(0.066)	(0.340)
8	1.037	1.025	1.036	0.997	1.279
	(0.066)	(0.072)	(0.066)	(0.066)	(0.343)
9	1.15	1.134	1.154	1.138	1.391
	(0.066)	(0.068)	(0.065)	(0.070)	(0.328)
10	1.429	1.431	1.43	1.399	1.669
	(0.037)	(0.034)	(0.038)	(0.035)	(0.336)
violent prior	0.036	0.035	0.036	0.041	0.034
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
drug prior	0.089	0.092	0.089	0.104	0.085
	(0.047)	(0.049)	(0.048)	(0.048)	(0.044)
dui3	-0.131	-0.118	-0.131	-0.147	-0.135
	(0.061)	(0.060)	(0.061)	(0.065)	(0.061)
recid1buckets					
1	0.641	0.652	0.646	0.627	0.633
	(0.051)	(0.051)	(0.051)	(0.053)	(0.055)
2	0.572	0.583	0.575	0.532	0.561
	(0.068)	(0.067)	(0.069)	(0.060)	(0.071)
3	0.446	0.456	0.448	0.408	0.439
	(0.052)	(0.052)	(0.053)	(0.049)	(0.055)
4	0.276	0.284	0.279	0.24	0.267
	(0.055)	(0.056)	(0.055)	(0.057)	(0.059)
5	0.251	0.258	0.251	0.22	0.237
	(0.050)	(0.053)	(0.050)	(0.052)	(0.050)
6	0.269	0.277	0.271	0.244	0.264
	(0.050)	(0.056)	(0.050)	(0.051)	(0.052)
7	0.258	0.265	0.259	0.235	0.256
	(0.047)	(0.049)	(0.047)	(0.045)	(0.047)
8	0.132	0.151	0.133	0.104	0.124
	(0.049)	(0.049)	(0.050)	(0.046)	(0.051)
9	0.021	0.04	0.021	0	0.011
	(0.058)	(0.060)	(0.059)	(0.057)	(0.059)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)

recid2buckets					
1	0.587	0.596	0.592	0.567	0.592
	(0.070)	(0.067)	(0.072)	(0.070)	(0.063)
2	0.647	0.652	0.651	0.633	0.616
	(0.064)	(0.060)	(0.066)	(0.051)	(0.059)
3	0.413	0.415	0.416	0.399	0.407
	(0.068)	(0.067)	(0.069)	(0.063)	(0.068)
4	0.377	0.396	0.378	0.339	0.341
	(0.095)	(0.095)	(0.095)	(0.089)	(0.097)
5	0.418	0.431	0.421	0.4	0.417
	(0.064)	(0.064)	(0.065)	(0.066)	(0.066)
6	0.165	0.184	0.168	0.167	0.15
	(0.055)	(0.057)	(0.055)	(0.055)	(0.055)
7	0.246	0.252	0.245	0.228	0.212
	(0.081)	(0.083)	(0.080)	(0.074)	(0.071)
8	0.156	0.163	0.158	0.155	0.136
	(0.062)	(0.061)	(0.062)	(0.062)	(0.064)
9	0.083	0.087	0.083	0.078	0.043
	(0.075)	(0.078)	(0.076)	(0.074)	(0.071)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	0.018	0.011	0.018	0.022	0.021
	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)
age	-0.015	-0.015	-0.015	-0.015	-0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	0.004	0.004	0.004	0.007	0.003
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
unemployment %	-0.043	-0.047	-0.042	-0.046	-0.045
	(0.024)	(0.024)	(0.024)	(0.023)	(0.025)
predict: on247					
thresh25	0.847	0.845	0.852	0.885	0.847
	(0.129)	(0.128)	(0.131)	(0.132)	(0.129)
thresh10					
thresh40					

priors						
	1	(base)	(base)	(base)	(base)	0.837
						(0.707)
	2	0.055	0.04	0.055	0.037	0.893
		(0.033)	(0.033)	(0.033)	(0.032)	(0.711)
	3	0.037	0.012	0.038	0.004	0.875
		(0.031)	(0.037)	(0.032)	(0.028)	(0.704)
	4	0.102	0.078	0.105	0.063	0.94
		(0.043)	(0.046)	(0.043)	(0.043)	(0.706)
	5	-0.011	-0.042	-0.006	-0.067	0.827
		(0.046)	(0.042)	(0.044)	(0.049)	(0.714)
	6	0.017	-0.003	0.021	-0.031	0.857
		(0.054)	(0.050)	(0.052)	(0.049)	(0.713)
	7	-0.07	-0.066	-0.071	-0.134	0.769
		(0.095)	(0.089)	(0.099)	(0.103)	(0.727)
	8	-0.061	-0.127	-0.065	-0.123	0.775
		(0.090)	(0.085)	(0.090)	(0.088)	(0.722)
	9	-0.103	-0.138	-0.083	-0.147	0.736
		(0.067)	(0.071)	(0.064)	(0.062)	(0.698)
	10	-0.099	-0.109	-0.093	-0.165	0.74
		(0.073)	(0.072)	(0.072)	(0.075)	(0.710)
violent prior		-0.02	-0.016	-0.019	-0.015	-0.021
		(0.031)	(0.029)	(0.030)	(0.032)	(0.031)
drug prior		-0.036	-0.023	-0.041	-0.019	-0.036
		(0.038)	(0.039)	(0.038)	(0.040)	(0.038)
dui3		0.408	0.396	0.406	0.393	0.404
		(0.096)	(0.093)	(0.100)	(0.099)	(0.096)
recid1buckets						
	1	0.137	0.135	0.162	0.109	0.129
		(0.124)	(0.125)	(0.122)	(0.128)	(0.123)
	2	0.142	0.138	0.154	0.078	0.154
		(0.117)	(0.119)	(0.116)	(0.120)	(0.116)
	3	0.177	0.18	0.189	0.117	0.174
		(0.116)	(0.127)	(0.119)	(0.112)	(0.120)
	4	0.202	0.207	0.215	0.146	0.206
		(0.086)	(0.092)	(0.086)	(0.084)	(0.084)
	5	0.193	0.171	0.191	0.139	0.193
		(0.087)	(0.092)	(0.088)	(0.084)	(0.095)

6	0.126	0.117	0.134	0.078	0.124
	(0.083)	(0.092)	(0.085)	(0.084)	(0.078)
7	0.105	0.087	0.11	0.057	0.112
	(0.062)	(0.073)	(0.061)	(0.059)	(0.062)
8	0.134	0.126	0.143	0.092	0.134
	(0.060)	(0.066)	(0.057)	(0.059)	(0.059)
9	0.039	0.032	0.04	0.006	0.037
	(0.048)	(0.049)	(0.048)	(0.047)	(0.047)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
recid2buckets					
1	-0.066	-0.051	-0.042	-0.113	-0.073
	(0.111)	(0.112)	(0.110)	(0.111)	(0.111)
2	0.031	0.037	0.048	0.006	0.036
	(0.090)	(0.095)	(0.089)	(0.099)	(0.087)
3	-0.039	-0.033	-0.026	-0.064	-0.051
	(0.083)	(0.077)	(0.082)	(0.083)	(0.091)
4	0.07	0.076	0.077	0.006	0.095
	(0.174)	(0.176)	(0.175)	(0.185)	(0.166)
5	0.267	0.263	0.284	0.232	0.283
	(0.126)	(0.125)	(0.121)	(0.127)	(0.130)
6	0.279	0.292	0.292	0.289	0.286
	(0.079)	(0.083)	(0.075)	(0.084)	(0.073)
7	0.357	0.34	0.356	0.341	0.37
	(0.108)	(0.105)	(0.105)	(0.109)	(0.114)
8	0.173	0.162	0.184	0.184	0.15
	(0.069)	(0.072)	(0.066)	(0.070)	(0.066)
9	0.146	0.145	0.147	0.154	0.163
	(0.074)	(0.082)	(0.075)	(0.075)	(0.069)
10	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
male	-0.092	-0.095	-0.088	-0.086	-0.092
	(0.046)	(0.047)	(0.047)	(0.040)	(0.046)
age	-0.002	-0.002	-0.002	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
police per capita	0.064	0.059	0.065	0.066	0.063
	(0.038)	(0.038)	(0.039)	(0.039)	(0.038)
unemployment	-0.06	-0.071	-0.058	-0.067	-0.059

%

	(0.049)	(0.048)	(0.049)	(0.050)	(0.049)
Statistics					
N	14518	14320	14518	14518	14530
ρ	0.09	0.125	0.089	0.08	0.05

	biprobit : limited crim history	biprobit : 10% threshold	biprobit : 40% threshold
predict: recid3			
on247	-0.29	-0.365	-0.294
	(0.138)	(0.131)	(0.116)
priors			
1		(base)	(base)
2		0.266	0.266
		(0.036)	(0.037)
3		0.447	0.447
		(0.030)	(0.030)
4		0.675	0.674
		(0.042)	(0.042)
5		0.715	0.716
		(0.068)	(0.068)
6		0.854	0.855
		(0.063)	(0.064)
7		1.117	1.119
		(0.067)	(0.068)
8		1.036	1.039
		(0.066)	(0.066)
9		1.149	1.152
		(0.066)	(0.065)
10		1.427	1.43
		(0.037)	(0.036)
violent prior		0.036	0.037
		(0.024)	(0.024)
drug prior		0.089	0.09

		(0.047)	(0.047)
dui3	0.17	-0.128	-0.134
	(0.050)	(0.060)	(0.062)
recid1buckets			
1	0.464	0.641	0.64
	(0.047)	(0.051)	(0.050)
2	0.392	0.572	0.572
	(0.058)	(0.067)	(0.068)
3	0.287	0.447	0.446
	(0.046)	(0.052)	(0.052)
4	0.129	0.277	0.275
	(0.052)	(0.055)	(0.055)
5	0.136	0.252	0.25
	(0.047)	(0.050)	(0.050)
6	0.171	0.269	0.269
	(0.047)	(0.050)	(0.049)
7	0.168	0.259	0.258
	(0.047)	(0.047)	(0.047)
8	0.081	0.132	0.131
	(0.044)	(0.049)	(0.050)
9	-0.025	0.021	0.021
	(0.052)	(0.058)	(0.058)
10	(omitted)	(omitted)	(omitted)
recid2buckets			
1	0.425	0.586	0.588
	(0.059)	(0.069)	(0.070)
2	0.508	0.646	0.647
	(0.052)	(0.064)	(0.064)
3	0.307	0.412	0.414
	(0.053)	(0.068)	(0.068)
4	0.271	0.377	0.376
	(0.081)	(0.096)	(0.095)
5	0.334	0.42	0.415
	(0.061)	(0.064)	(0.064)
6	0.092	0.167	0.162
	(0.056)	(0.055)	(0.053)
7	0.15	0.248	0.242
	(0.064)	(0.082)	(0.081)

8	0.088	0.157	0.154
	(0.057)	(0.062)	(0.061)
9	0.044	0.084	0.082
	(0.068)	(0.075)	(0.075)
10	(omitted)	(omitted)	(omitted)
male	0.077	0.017	0.019
	(0.019)	(0.019)	(0.019)
age	-0.018	-0.015	-0.015
	(0.001)	(0.001)	(0.001)
police per capita	0.008	0.005	0.004
	(0.012)	(0.011)	(0.011)
unemployment %	-0.041	-0.043	-0.042
	(0.024)	(0.024)	(0.024)
predict: on247			
thresh25	0.845		
	(0.129)		
thresh10		0.854	
		(0.137)	
thresh40			0.856
			(0.098)
priors			
1		(base)	(base)
2		0.05	0.058
		(0.033)	(0.034)
3		0.038	0.042
		(0.031)	(0.032)
4		0.1	0.109
		(0.043)	(0.043)
5		-0.013	-0.005
		(0.046)	(0.046)
6		0.016	0.027
		(0.053)	(0.055)
7		-0.065	-0.062
		(0.096)	(0.094)
8		-0.062	-0.057

		(0.088)	(0.090)
9		-0.105	-0.092
		(0.067)	(0.067)
10		-0.098	-0.078
		(0.073)	(0.071)
violent prior		-0.018	-0.029
		(0.030)	(0.031)
drug prior		-0.03	-0.041
		(0.037)	(0.039)
dui3	0.416	0.402	0.406
	(0.099)	(0.095)	(0.097)
recid1buckets			
1	0.144	0.136	0.135
	(0.122)	(0.123)	(0.125)
2	0.153	0.139	0.14
	(0.114)	(0.118)	(0.119)
3	0.189	0.174	0.18
	(0.114)	(0.118)	(0.118)
4	0.214	0.205	0.209
	(0.086)	(0.085)	(0.087)
5	0.205	0.191	0.191
	(0.087)	(0.088)	(0.091)
6	0.135	0.126	0.131
	(0.081)	(0.083)	(0.085)
7	0.117	0.1	0.105
	(0.060)	(0.064)	(0.063)
8	0.138	0.133	0.142
	(0.060)	(0.061)	(0.060)
9	0.046	0.038	0.04
	(0.047)	(0.048)	(0.050)
10	(omitted)	(omitted)	(omitted)
recid2buckets			
1	-0.055	-0.059	-0.069
	(0.106)	(0.110)	(0.108)
2	0.039	0.034	0.025
	(0.090)	(0.089)	(0.089)
3	-0.032	-0.032	-0.044

	(0.077)	(0.083)	(0.083)
4	0.077	0.071	0.079
	(0.171)	(0.175)	(0.173)
5	0.269	0.277	0.27
	(0.122)	(0.126)	(0.123)
6	0.281	0.287	0.278
	(0.080)	(0.079)	(0.077)
7	0.361	0.35	0.353
	(0.105)	(0.110)	(0.111)
8	0.173	0.177	0.173
	(0.068)	(0.069)	(0.068)
9	0.148	0.152	0.158
	(0.076)	(0.077)	(0.074)
10	(omitted)	(omitted)	(omitted)
male	-0.099	-0.095	-0.091
	(0.046)	(0.046)	(0.046)
age	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
police per capita	0.062	0.067	0.055
	(0.038)	(0.040)	(0.034)
unemployment %	-0.057	-0.043	-0.059
	(0.049)	(0.048)	(0.048)
Statistics			
N	14518	14518	14518
ρ	0.061	0.11	0.065