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Quantifying the Specific Deterrent Effects of DNA Databases

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Abstract

Forensic science has come to play an increasingly important role in aiding criminal investigations. The field has experienced numerous advances over the last two decade. This has lead courts, practitioners, prosecutors and legislators to embrace the tools it offers, in general, and DNA profiling, in particular. The National Institute of Justice consequently sought applications to study a broad array of social science research issues that these advances have raised. This report describes findings from a project aimed at quantifying the specific deterrent effects of DNA databases.

Re-offending patterns of a large cohort of offenders released from Florida Department of Corrections custody between 1996 and 2004 were analyzed. During this period, several important pieces of legislation were passed in Florida requiring convicted felons—convicted of an increasing number of crime types—to submit biological samples for DNA profile extraction and storage in searchable databases.

Models constructed to identify the specific deterrent effects of DNA databases distinct from their probative effects yielded mixed results. Small deterrent effects—2 to 3 percent reductions in recidivism risk attributable to deterrence—were found for only offense categopries (robbery and burglary). Strong probative effects—20 to 30 percent increase in recidivism risk attributable to probative effects—were uncovered for most offense categories. Methods, data, results and implications are discussed in this report.

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At the Urban Institute, Jennifer Yahner, Mark Coggeshall, and Kevin Roland provide invaluable research support at various times during this research effort. Jennifer helped process all the data and provided keen insights into data peculiarities. Mark was instrumental in helping define the cohort and outcomes. Both Jennifer and Mark provided valuable feedback that has helped shape the analysis reported here. I thank two anonymous reviewers for their insightful comments.

The views expressed here are solely the author's and do not represent the official policies or position of the U.S. Department of Justice, the Urban Institute (including its trustees and funders), the Florida State University, the Florida Department of Corrections, the Florida Department of Law Enforcement, or any person named above.

Executive Summary

OVERVIEW

The news brings almost daily affirmation of the potential of forensic science, generally, and deoxyribonucleic acid (DNA) profiling, in particular, to aid criminal investigations and exculpate the wrongfully convicted. The ability of DNA evidence to place persons at crime scenes with near certainty is broadly accepted by criminal investigators, courts, policymakers, and the public. In response to this premise, numerous law enforcement agencies have established "cold case" units to use forensic evidence to investigate long-unsolved serious crimes and have instituted policies calling for the collection and preservation of forensic evidence from many types of crime scenes. Court systems are generally accepting of the probative value of DNA evidence. As a result, legislators in all 50 states have established DNA databases and have gradually widened the categories of offenders and suspects whose DNA profiles may be stored. Despite that, the public safety benefits of such large-scale investments are largely unknown and research attempting to quantify these benefits is only gradually emerging.

This report documents findings from a project designed to quantify the effect of the embrace of DNA technology on offender behavior. In particular, researchers examined whether an offender's knowledge that their DNA profile has been entered into a database deters them from offending in the future. Briefly, the logic of the hypothesis that DNA databases may exert specific deterrence effects is as follows: The offender knows that his or her DNA profile has been entered into a database and believes that this fact increases the probability that he or she will be apprehended and punished for any future offense. Since the perceived certainty of punishment for future offending is now greater, deterrence theory suggests that the offender will respond by reducing his/her rate of offending. This study tests the hypothesis, and quantifies any specific deterrent effects, by examining the re-offending behavior of a cohort of offenders whose profiles were entered into Florida's DNA Investigative Support Database.

Florida's DNA database is among the oldest and largest of the 50 state DNA databases. First authorized by the Florida legislature in 1989, the first profile was entered into the database in 1990. The original legislation authorized the entry of profiles of persons convicted of certain sex offenses during or after 1990. Since then, the criteria have been expanded to include persons convicted of homicide (1993); carjacking, home invasion robbery, and aggravated battery (1995); adjudicated juveniles (1995); burglary (2000); robbery (2002); kidnapping and manslaughter (2003); forcible felonies and firearm violations (2004); and all felonies (2005). Amendments passed in 1995 also authorized the entry of profiles of persons convicted of qualifying offenses regardless of conviction date provided the offender remained under the supervision of the state of Florida.

BACKGROUND

DNA databases leverage standardization and ubiquitous computer database and networking technologies to make forensic science a formidable investigative technology. A biological specimen (e.g., saliva, blood, semen, or skin cells) is collected from a crime scene. Laboratory analysis extracts the DNA from the nucleus of the cells in the specimen and, in a process known as short tandem repeat (STR) analysis, identifies 13 specific segments from the sample DNA that are known to be highly heterogeneous in the population. Information about these 13 segments, or markers, is submitted as a DNA profile for entry into a local DNA database. Profiles in local databases that meet the relevant criteria, are included in the state's DNA database.

Each database is composed of two indexes, or sets of profiles. One index includes profiles from identified persons (e.g., convicted or suspected offenders compelled by state law to submit a profile to the database) and the other includes profiles from samples collected from crime scenes where no suspect has been identified. Thus, there are two means by which DNA evidence collected from a crime scene may lead to the identification of a suspect: (1) the crime scene evidence may be matched to the profile of a known offender or (2) the crime scene evidence may be matched to a profile from another crime scene creating an opportunity for investigators in both cases to collaborate.

MOTIVATION

There is no doubt that forensic evidence, particularly DNA profiles, have huge probative value. Conviction of guilty offender because of DNA evidence, identification of suspects because of solved "cold cases", and exoneration of the wrongfully convicted are well documented benefits of this trend. Given the near certainty with which DNA identifies and places suspects near the scene of a crime, might these benefits not deter offenders who know that their DNA profile exists in a searchable database? Indeed, legislation sometimes explicitly identifies specific deterrence as a reason for expanding the coverage of these DNA profile databases.

Deterrence theory certainly suggest that specific deterrent effects should materialize. Owing to its demonstrated probative value, it is plausible to believe that offenders are keenly aware that DNA evidence assists tremendously in solving crimes and in prosecuting suspects. The swiftness and the certainty of punishment is clearly many fold when DNA matched evidence is utilized. Therefore, knowledge about the fact that one's DNA profile exists in a database to be conveniently searched at a later date should deter these offender (at least on the margin). Hence, specific deterrence effects are very plausible.

METHODOLOGY

Given the inherent difficulty (ethical and practical) in randomly assigning offenders to cleverly conceived treatment and comparison groups for the purpose of inferring specific deterrence and probative effects of DNA databases, this research effort developed an alternate strategy for extracting these effects from transactional data. The strategy is based on observational data.

Re-offending is a phenomenon typically recorded, modeled, and studied as event histories. All event history data are measured from some reference point. For the case of criminal recidivism, several clocks are possible to define. Examples include time since birth, time since first event, time since last event, time since prison release, etc. The identification strategy used in this research effort was based on linking the two simultaneous effects of DNA databases—specific deterrence and probative—to different clocks measuring the same observed events. The age-based clock was used to identify specific deterrent effects and the spell-based clock to identify probative effects. These were motivated by the observation that any interruption in the age-based clock that can be linked to DNA databases could be construed as affecting the criminal career of an individual; and any interruptions in the spell-based clock that could be linked to DNA databases could be construed as short-term changes in offending patterns that were net of any criminal career changes. Since the unfolding of a criminal career can most closely be associated with an individual's choices, any changes that DNA databases bring to these unfolding careers is identified as the specific deterrence effect.

Since the two clocks are different ways of measuring the same events, the multiple-clock models need to be estimated simultaneously. Moreover, a flexible functional form is considered desirable as theory provides little guidance as to the form of the trajectories other than that they are parabolic in shape. Consequently, a semi-parametric approach was developed for estimating the models. Despite its flexibility, the framework provides a sufficiently rich apparatus to conduct hypothesis tests relating to the various processes.

The hazard of recidivism within a three year follow-up period (after release from prison) was the key outcome measure and the estimated models linked this hazard to duration since release from prison as well as duration since birth. Each of these processes were allowed to have a parabolic shape and each of them was permitted to vary by treatment status—whether or not a released offender had his/her DNA profile stored in a searchable database. The strategy allows DNA databases to have three distinct effects on the evolution of the hazard as time since release unfolds. First, the treatment and control groups are permitted to differ, in the aggregate, for unexplained reasons (i.e., start at different intercepts). Second, they are permitted to evolve differently as duration since release unfolds. Finally, they are permitted to evolve differently as each of the sample members age. Only those changes that affect the latter two dynamic processes are identified as quantities of interest. Once isolated in this manner, the specific deterrence and probative effects are then aggregated over the follow-up period to estimate the net effects over the entire follow-up period.

DATA

All offenders released from the Florida Department of Corrections (FDOC) between January 1996 through December 2004 were considered eligible. For each individual in the cohort, criminal history records from a matched criminal history file provided by the Florida Department of Law Enforcement (FDLE) were obtained. A small number of sample members for whom matched criminal history records were not available were dropped from the study. Also, offenders not released to Florida communities (i.e., those released to other states or countries) were also excluded from the analysis as the FDLE criminal history file only contains Florida arrest records. For offenders released multiple times during the 1996–2004 period, all episodes were retained in the analysis.

The treatment group was composed of all releasees who had their DNA entered in a database at some point prior to their release from prison. The control group was composed of all releasees who did not have their DNA entered in a database until either being rearrested after release or as of the end of the three-year follow-up period.

Two different outcomes were analyzed. First, the FDLE criminal history records were used to define rearrest within three years of release as an outcome. The arrest date was used to flag the recidivism event and compute duration on various clocks. Second, court docket information maintained by the FDOC was used to define a reconviction outcome, also within a three-year follow-up period. For the reconviction outcome, the offense date was used to flag the recidivism event and compute duration on various clocks. The reconviction outcome therefore flags re-offending events that ultimately led to a conviction.

Six offense groups were created to stratify the analysis by. These included offenders who were released after being incarcerated primarily on Violent charges (including murder, manslaughter, sexual offenses, and other violent offenses); Robbery; Burglary; Other Property charges (including theft, fraud, and damage); Drug related charges; and Other charges (including weapons and other public order offenses). A host of demographic and related attributes were also extracted from the data.

FINDINGS

Since interest centers around the estimation of multiple-clock models, conditional on treatment status, the first step in the analysis was to assess the extent to which the attributes of the two groups differed. If they did, then Inverse Probability of Treatment weights were used to balance the samples. Logistic regression models were estimated (for each offense category and outcome type) that predicted the probability of each sample unit having DNA evidence in a database prior to release. Predicted group membership probabilities were then inverted and normalized to create the weights. All subsequent analysis were done using these weights.

Available attributes included time served prior to release, age at release, criminal history (total number of prior arrests), supervision status at release, gender, race, ethnicity, highest education level attained, and employment status (prior to incarceration). Comparison of the attributes before and after weighting suggest that the imbalance between the two groups (in terms of the observable attributes) that did exist was largely accounted for.

Despite balancing on available attributes, the treatment and control groups differred in the average recidivism rates, over and above what was attributable to the specific deterrent and probative effects. Parameters related to the age-based clock implied a traditional age-crime relationship whereas the spell-based clock parameters were mixed across offense-specific models. That is, the age-based process typically increased with age and then declined at some point. The spell-based hazard paths were either increasing in spell length at a decreasing rate or were decreasing in spell length at a decreasing rate. More importantly, however, parameters on the treatment indicator generally (not always) suggested that being released from prison with DNA in a searchable database typically slowed down the age-based process but sped up the spell-based process. These are consistent with the specific deterrent and probative effects of DNA databases. Overall findings are summarized below:

- There is evidence of the specific deterrence effect. Findings were particularly interesting for robbery and burglary. They were both in the expected direction—negative effects implying a deterrence effect—and were statistically significant.

- There was even stronger evidence for the probative effects. Findings showed that most of the computed probative effects were in the expected direction—positive effects implying increased recidivism—and were fairly large. Most were statistically significant as well.

- Some of the specific deterrence effects recovered were perversely signed. That is, the net effects of DNA databases that is attributable to specific deterrence was found to be positive. The probative effects were pretty consistently in the correct direction.

- Where they were in the correct direction, and statistically significant, the specific deterrence effects and the probative effects were of a magnitude very similar to findings reported by the U.K. Home Office (Home Office 2004). Specific deterrence effects were in the range of 2 to 3 percent (the Home Office study documented roughly 1 percent) and the probative effects were in the 20 to 40 percent range (the Home Office study documented about 20 percent).

IMPLICATIONS

This study was designed to assess and quantify the deterrent effects of DNA databases on offender behavior. Based on the findings, we may answer the two important, and related, policy questions:

1. Do DNA databases provide indirect benefits like deterring convicted offenders from committing future crimes?

2. Should state legislatures continue to expand coverage of DNA databases?

The answer to the first question, based on this study, is mixed. Perhaps for some types of crimes there are stronger deterrent effects than others. Clearly, property crimes like robbery and burglary show deterrence effects. There is nearly a 2 to 3 percent reduction in recidivism events over the follow-up period that can be attributed to specific deterrence.

The answer to the second question is more clear. If, as was uncovered in this study and in the U.K. Home Office study, the specific deterrence effects of DNA databases are small, then sacrificing these effects for the huge probative benefits that research (including this study) has clearly demonstrated time and again, may be well worth it. As such, the trade-off is clearly in favor of future expansion of the realm of crimes and category of offenders covered by DNA databases.

Chapter 1

Introduction

The news brings almost daily affirmation of the potential of forensic science, generally, and deoxyribonucleic acid (DNA) profiling, in particular, to aid criminal investigations and exculpate the wrongfully convicted. The case of Jerry Buck Inman, a registered sex offender in Florida and resident of Tennessee, is illustrative. In June 2006, he was arrested in Tennessee in connection with the kidnapping, rape, and murder of a Clemson University student in South Carolina after DNA evidence collected at the crime scene was matched to his profiles in DNA databases maintained by the states of Florida and North Carolina (FDLE 2006).

The ability of DNA evidence to place persons at crime scenes with near certainty is broadly accepted by criminal investigators, courts, policymakers, and the public. In response to this premise, numerous law enforcement agencies have established "cold case" units to use forensic evidence to investigate long-unsolved serious crimes (Kirsch 2006) and have instituted policies calling for the collection and preservation of forensic evidence from many types of crime scenes. Court systems are generally accepting of the probative value of DNA evidence (Palermo 2006). As a result, legislators in all 50 states have established DNA databases and have gradually widened the categories of offenders and suspects whose DNA profiles may be stored. Despite that, the public safety benefits of such large-scale investments are largely unknown and research attempting to quantify these benefits is only gradually emerging.

In response to growing public awareness, and the numerous advances that have been made in forensic sciences over the last decade, the National Institute of Justice solicited applications for conducting research on a broad array of emerging social science issues in forensic science to inform precisely such unanswered questions. The Urban Institute proposed and was awarded a grant to quantify the specific deterrent effects of DNA databases.

This report documents findings from that project designed to quantify the effect of the embrace of DNA technology on offender behavior. In particular, researchers examined whether an offender's knowledge that their DNA profile has been entered into a database deters them from offending in the future. Briefly, the logic of the hypothesis that DNA databases may exert specific deterrence effects is as follows: The offender knows that his or her DNA profile has been entered into a database and believes that this fact increases the probability that he or she will be apprehended and punished for any future offense. Since the perceived certainty of punishment for future offending is now greater, deterrence theory suggests that the offender will respond by reducing his/her rate of offending. This study tests the hypothesis, and quantifies any specific deterrent effects, by examining the re-offense behavior of a cohort of offenders whose profiles were entered into Florida's DNA Investigative Support Database.

Unfortunately, because punishment can be swifter and more certain, it becomes very challenging to use recidivism data to isolate and identify the specific deterrent effects of DNA databases from their probative effects. This study relied on a multiple-clock model to help identify these two effects. In addition, since it relied exclusively on observational data, it utilized an Inverse Probability of Treatment Weighting procedure to balance the samples on all observable and relevant attributes.

Findings are mixed. Small specific deterrent effects were uncovered for some crime categories. This includes burglary and robbery. However, for some crime categories, the effects were perversely signed (positive effects). The probative effects comported more with expectations. Most models suggested positive and relatively large probative effects.

The report is organized as follows: The next chapter provides background information. This is followed by a description of the methodology used to identify and estimate the effects of DNA databases in chapter 3. The data are described in chapter 4. Main findings are reported and discussed in chapter 5. This includes parameter estimates as well as the implied specific deterrent and probative effects of DNA databases. The report concludes with a discussion of the findings and implications for policy and practice in chapter 6. Technical materials and detailed models estimates are provided in appendices.

Chapter 2

Background

2.1. DNA DATABASES

DNA databases leverage standardization and ubiquitous computer database and networking technologies to make forensic science a formidable investigative technology. A biological specimen (e.g., saliva, blood, semen, or skin cells) is collected from a crime scene. Laboratory analysis extracts the DNA from the nucleus of the cells in the specimen and, in a process known as short tandem repeat (STR) analysis, identifies 13 specific segments from the sample DNA that are known to be highly heterogeneous in the population (Kirsch 2006). Information about these 13 segments, or markers, is submitted as a DNA profile for entry into a local DNA database. Profiles in local databases that meet the relevant criteria, are included in the state's DNA database.

Each database is composed of two indexes, or sets of profiles. One index includes profiles from identified persons (e.g., convicted or suspected offenders compelled by state law to submit a profile to the database) and the other includes profiles from samples collected from crime scenes where no suspect has been identified. Thus, there are two means by which DNA evidence collected from a crime scene may lead to the identification of a suspect: (1) the crime scene evidence may be matched to the profile of a known offender or (2) the crime scene evidence may be matched to a profile from another crime scene creating an opportunity for investigators in both cases to collaborate (Office of the U.S. Attorney General n.d.).

Since 1990, the federal government has maintained a distributed DNA database called the Combined DNA Index System (CODIS) that includes three tiers of DNA profiles. The national tier is composed of profiles collected by federal law enforcement agencies, the state tier links the databases of the 50 states, and the local tier does the same for participating local DNA databases (FBIa n.d.). The hierarchy of the tiered system permits each state and locality to set its own criteria for determining which profiles to include, and the distributed nature of the database means that each participating state and locality maintains direct control over its own profiles.

The national tier of CODIS includes more than 4 million offender profiles and more than 150,000 forensic profiles from open investigations (FBIa n.d.). The effectiveness of DNA databases as investigative tools is proportional to their scale. Each new profile entered increases the probability that the next search will yield a match.

This comes at a cost, though. The growth of the DNA database is limited by the scarcity of laboratory capacity to process the samples. According to one estimate, there is a national backlog of approximately 300,000 samples awaiting analysis and entry (Zedlewski and Murphy 2006). As a result of the backlog and the constant inflow of persons with new qualifying convictions, the number of profiles in the DNA databases will continue to grow for the foreseeable future even if no changes are made to the eligibility criteria and no additional resources are devoted to expand laboratory capacity.

These increases can have other non-monetary costs as well. Taylor et al. (2006) argue, for example, that widening the net too wide too fast can actually diminish any specific deterrent effects because of the sheer size of the backlog—in effect overwhelming the system.

2.2. FLORIDA CONVICTED OFFENDER DATABASE

Florida's DNA database is among the oldest and largest of the 50 state DNA databases. According to the FBI, Florida's database contributes more than 325,000 profiles of convicted offenders to the national tier of CODIS, and Florida's database has aided more than 5,000 investigations (FBIb n.d.). First authorized by the Florida legislature in 1989, the first profile was entered into the database in 1990. The original legislation authorized the entry of profiles of persons convicted of certain sex offenses during or after 1990. Since then, the criteria have been expanded to include persons convicted of homicide (1993); carjacking, home invasion robbery, and aggravated battery (1995); adjudicated juveniles (1995); burglary (2000); robbery (2002); kidnapping and manslaughter (2003); forcible felonies and firearm violations (2004); and all felonies (2005). Amendments passed in 1995 also authorized the entry of profiles of persons convicted of qualifying offenses regardless of conviction date provided the offender remained under the supervision of the state of Florida (FDLE n.d.). The Florida Department of Law Enforcement (FDLE), which maintains the state's DNA database, expects to add 36,000 profiles to the database in each of the next several years (FDLE 2006).

2.3. DETERRENCE THEORY

Cesare Beccaria is often cited as the progenitor of deterrence theory. Beccaria (1764) argued that deterrence was the fundamental justification for punishment: "The aim, then, of punishment can only be to prevent the criminal committing new crimes against his countrymen, and to keep others from doing likewise" [49]. He also pointed to three characteristics of punishment that contribute to its effectiveness as a deterrent: severity ("For a punishment to be efficacious, it is enough that the disadvantage should exceed the advantage anticipated from the crime" [50]), certainty ("One of the greatest checks upon crime is not the cruelty of punishment but its inevitability" [68]), and celerity ("The more prompt the punishment and the sooner it follows the crime, the more just it will be and the more effective" [65]).

Since Beccaria's time, scores of empirical studies have tested elements of his theory. Paternoster (1987) concluded, based on his review of the literature, that punishment severity was unlikely to deter offending. Consistent with this view, subsequent research has found that the certainty of sanction is a greater deterrent to offending than either the severity (Nagin and Pogarsky 2001, 2003) or swiftness of the sanction (Nagin and Pogarsky 2001). Paternoster (1987) also concluded that the time ordering of the variables is vital to any test of the deterrence hypothesis. Deterrent effects, which are the influence of present perceptions of punishments and rewards on future offending, must be distinguished from "experiential effects" (i.e., the effect of prior offending on present perceptions).

Deterrence and experiential effects have very different implications for policymaking, and Carmichael and Piquero (2006) recently found evidence of both an experiential effect and a deterrent effect of sanction certainty in a single sample. The evidence suggesting that both deterrent and experiential effects may be at play, combined with evidence that individuals' perceptions of sanction risk are not stable over time, suggests that cross-sectional tests of deterrence are inadequate (Paternoster 1987).

More recently, the deterrence literature has produced evidence of population heterogeneity on several key constructs relevant to deterrence theory. One such finding suggests that persons may vary in the malleability of their perceptions of sanction risk (Marlowe et al. 2005). Persons also differ in the responsiveness of their offending behavior to their perceptions of sanction risk (Pogarsky, 2002). This emerging research suggests that the least deterrable persons are those with strong moral inhibitions against offending (Pogarsky 2002; Pogarsky, Kim, and Paternoster 2005; Tittle and Botchkovar 2005) and that more crime-prone persons may be more sensitive to deterrence (Wright et al. 2005; Tittle and Botchkovar 2005). Pogarsky (2002) also found that punishment severity may be as or more important than punishment certainty among the most deterrable persons.

Another facet of the theme of population heterogeneity in deterrability concerns the process by which information about official sanctions affects perceptions of sanction risk. Pogarsky, Piquero, and Paternoster (2004) modeled this process and found that it is conditioned by the level of sanction risk perceived at baseline, as well as information about the offending and sanctioning of peers. Persons with low perceptions of sanction risk at baseline and who subsequently offended and were arrested showed large changes in their perceptions of sanction risk at follow-up. This is consistent with the authors' hypothesis that the experience would yield a large change in perceived risk because the sanction was at odds with expectations. Pogarsky et al. (2004) also found that persons with little offending experience of their own tended to rely on peer experiences to inform their perceptions of sanction risk, while persons with more personal offending experience tended to discount peer experiences.

The literature clearly suggests then that persons vary in the malleability of their perceptions of sanction risk and that contextual considerations (e.g., personal offending experience and peer offending experience) may affect the formation of sanction risk perceptions. Carmichael and Piquero (2004) found that situational factors, particularly emotional arousal, may also affect perceptions of sanction risk. Among subjects who perceived that they would be greatly angered by the circumstances in a vignette describing an assaultive scenario, formal sanction threat did not correlate with intention to attack (Carmichael and Piquero 2004). Perhaps this helps to explain Kane's (2006) finding that crimes motivated by pecuniary gain and which commonly occur in public view (i.e., robbery and burglary) may be more affected by deterrence than other types of offenses (e.g., assault) that are commonly perpetrated during moments of emotional arousal.

2.4. DETERRENCE AND DNA

Although questions about what types of persons and what types of circumstances will yield deterrence effects have been researched in some detail, little research has been done to investigate the effects of DNA evidence on investigations, case processing, and criminal offending. The United Kingdom's Home Office sponsored an evaluation of the effects of expanded forensic investigation of burglary, motor vehicle theft, and vehicle break-ins. The evaluation considered whether expanded use of DNA, tool mark, and footwear evidence collection would lead to higher rates of case closure and conviction and lower rates of crime. Of the forensic techniques studied, expanded use of DNA evidence yielded the largest improvements in outcomes. The evaluation found that expanded use of forensic techniques to the targeted crimes would lead to a 21 percent increase in suspect identifications and a 19 percent increase in convictions (Home Office 2004). The targeted categories of crime decreased about 1 percent in the treatment areas as compared with the comparison areas, but changes in overall crime levels favored the comparison areas (Home Office 2004). It is unclear whether public awareness of the evaluation, the targeted crimes, and the study area boundaries was sufficient to attribute these shifts to deterrent effects.

A second, small (n = 150) case-control study examined the effects of DNA evidence on court outcomes in homicide cases in Queensland, Australia. Briody (2004) found that cases with DNA evidence were more likely to be accepted for prosecution and more likely to end in conviction.

Similarly, in a more recent study undertaken by the Urban Institute, researchers conducted a prospective, randomized study of the cost-effectiveness of DNA in investigating high-volume crimes, including residential burglary, commercial burglary, and theft from automobiles (Roman et al. 2008). Biological evidence was collected at up to 500 crime scenes in each site between November 2005 and July 2007, and cases were randomly assigned to the treatment and control groups, producing a roughly equal split of cases within each site. In the treatment group, DNA processing as well as traditional practices were used to investigate the case. In the control group, biological evidence was not initially tested, and case outcomes were due only to traditional investigation. The study found, among other things, that (i) property crime cases where DNA evidence was processed have more than twice as many suspects identified, twice as many suspects arrested, and more than twice as many cases accepted for prosecution compared with traditional investigation, and (ii) DNA was at least five times as likely to result in a suspect identification compared with fingerprints.

These findings confirm that, as a prerequisite for the specific deterrent hypothesis, DNA evidence does increase the certainty and celerity of punishment at certain points in criminal case processing. Indeed the probative value of DNA evidence has been proven time and again.

Prior research on specific deterrence, in general, supports the plausibility of the hypothesis that an offender's knowledge that his/her DNA profile has been entered into a searchable database may increase the offender's perceived certainty of sanction and thereby deter their future offending. In other words, DNA databases ought to yield specific deterrent effects.

Chapter 3

Methods

As highlighted in the previous chapter, there are two—possibly simultaneous—effects that recording an individual's DNA profile into a database can create. First, there is the specific deterrent effect. Individuals who would have re-offended may now choose not to re-offend for fear of receiving swifter and more certain punishment. Second, there is the probative effect. Individuals that do re-offend will receive sanctions quicker and with more certainty.

Unfortunately, comparing the recidivism rates of individuals with and without DNA profiles entered in a searchable databases will yield some combination of these two effects. Furthermore, individuals with DNA profile entered in a databases may be markedly different from those whose DNA profile is not entered in the database. Hence, a third reason why individuals with or without DNA profiles entered in a searchable database may have different recidivism rates is because they may be sufficiently different in important attributes like criminal history, age, gender, and offense. This makes the task of identifying the specific deterrent effects of DNA databases particularly challenging.

This chapter describes the strategy used for identifying these distinct effects and then describes the strategy used for estimating the parameters needed to quantify these effects.

3.1. IDENTIFICATION STRATEGY

Let $r(t)$ denote the hazard of the recidivism outcome of interest (e.g., rearrest, reconviction, or reincarceration) at a particular time (t). Typically, the outcome of interest is measured over a finite follow-up period (e.g., three years) and the cohort of interest is defined in some manner (e.g., prison release or probation intake). For ease of exposition, in this chapter these definitions are left generic (they will be clarified in the data chapter). Let τ denote the *treatment* indicator—having one's DNA entered into a DNA database prior to becoming at risk of the recidivism event (e.g., prior to being released from prison).

3.1.1. A Thought Experiment

As a point of departure, consider the following thought experiment. Assume a randomized experiment was possible to implement. Assume that for all individuals being released from prison during a particular period, half were instructed to provide their biological samples for the purpose of extracting DNA profiles that would be recorded in a database and the other half were not required to provide any biological evidence. Assume also that the individuals in these groups were selected completed at random. As time since release unfolds, assume researchers tracked both groups and recorded their first recidivism event (e.g., reconviction or rearrest that eventually lead to a reconviction). Following standard investigative practices, assume that criminal justice authorities had made full use of the DNA databases in solving crimes and prosecuting suspects.

Despite the random experiment, using recidivism data alone it would not be possible to identify the deterrent effects of the database from their probative effect. If the deterrent effect exceeded the probative effect, then one would find that τ reduced recidivism rates. If, on the other hand, the deterrent effect was small compared to the probative effect, then one would find that τ increased recidivism rates. Therefore, a pure randomization, were it feasible, would help identify only the overall effect of DNA databases.

Could one devise an experiment that distinguishes the deterrent effects from the probative effects? In order to identify the pure probative effect, one could, for example, devise an experiment whereby DNA profiles were collected from all individuals but a randomly selected half were entered into a database and made available to criminal justice authorities. Hence all individuals would assume that their profile was available in a searchable databases so that any specific deterrent effect would be controlled for adequately. Now the difference between the treatment and comparison groups would identify the probative effect of DNA databases. Indeed the Urban Institute's prospective randomized experiment (Roman et al. 2008) was based on this identification strategy.[1]

Similarly, to identify the deterrent effects of DNA databases, one could devise an experiment whereby DNA evidence was collected from a random group of the subjects but the evidence was not entered into any databases (without their knowledge). Hence there would be no probative effect to be realized and any difference between the treatment and control groups could be identified as a specific deterrence effect.

These thought experiments suggest that the effects of DNA databases can be identified and isolated. However, conducting these experiments could be very costly and, in some cases, infeasible. It would be hard to justify holding back potential evidence (where available) for solving crimes and aiding prosecution, especially for prolonged periods of time (e.g., three year) while the study was conducted.[2] Moreover, if randomization itself was not possible, then there is the

[1]In the Urban Institute's randomized field experiment, biological evidence thought to contain human cells was collected from 500 property crime scenes. Researchers randomly divided the cases into treatment and control groups. In the treatment group, evidence was analyzed for DNA and if found, this was run through CODIS for a match. Therefore, traditional investigation techniques as well as DNA evidence was used. In the control group, only traditional investigation techniques were used (for a limited amount of time).

[2]For example, in the Urban Institute's field experiment, the crime scene evidence of the control group was not tested for DNA only for a period of two months. Officers were not told which cases were treatment and which were control. Traditional investigation techniques were employed in both cases: the only difference was whether DNA evidence was performed during the first two months (Roman et al. 2008:20).

possibility that the treated and untreated groups were different in unobservable ways thereby providing misleading inferences.

3.1.2. Multiple Clock Models

Are there other strategies that may help identify the deterrent effects from the probative effects of DNA databases? This study utilizes one such strategy. It relies on the concept of multiple-clocks to help identify the three effects of DNA databases on the recidivism hazards. That is, it first makes the case for linking the specific deterrent effects and the probative effects of DNA databases to different clocks measuring the same events. Multiple clock models then make it possible to extract the distinct effects from the same recidivism data.

Multiple clock models are simply a means of studying duration to failure measured on different clocks (Yamaguchi 1991:53; Lillard 1993). For example, when studying duration to first recidivism event—as is typically done in criminal justice research—one is implicitly measuring the duration to the event from the date of release (setting the clock to 0 at the time of release). If, instead, one were to study age at the first recidivism event, one would implicitly be measuring duration to the event from the date of birth (setting the clock to 0 on the individual's date of birth). Multiple-clock models allow one to study these two processes—the spell-based and the age-based—simultaneously as they unfold over the follow-up period to produce the recidivism events. Figure 3.1 shows how the same event can produce two different manifestations of the same underlying stochastic process.

How the hazard unfolds with age captures the criminal career-long component of the stochastic process, whereas its evolution with the spell-length is more immediate and narrow in scope. Both components are sub-trajectories that simultaneously result in the observed recidivism events. However, because the age-based component captures an unfolding career, one may associate that more directly with the offender's decision-making process. The spell-based process may be associated more directly with decisions made by others. Note that the

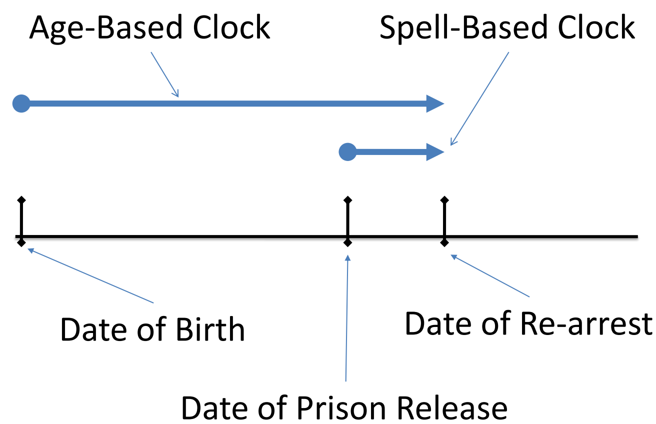

Figure 3.1: Measuring the same event on two clocks provides two related manifestations of one underlying stochastic process.

two are linked: distinctly associating each component with offenders and others is only possible if both are modeled simultaneously. Multiple-clock models are ideally suited to do just that—study stochastic processes along multiple clocks.

As a result, the effects of τ in modifying the age-based trajectory is used to identify the specific deterrent effect because it provides a way to quantify the criminal career difference between the treated and the untreated groups *while controlling the effects of* τ *on the spell-based clock*. Similarly, the effects of τ on the spell-based trajectory is used to identify the probative effect because it provides a way to quantify the pure immediate-term difference between the treated and the untreated groups *while controlling the effect of* τ *on the criminal career*.

It is also very likely—due to jurisdiction laws pertaining to the collection of DNA profiles—that important attributes are very different across the treated and the untreated groups. For example, current charge—which triggers collection of DNA in most states—is typically related to prior criminal history, age, and a host of other factors that are consistent predictors of the outcomes (recidivism). Therefore, in addition to the multiple-clock model, one needs to allow for these differences as well.

This study used two strategies to mitigate the ill-effects of sample imbalance—a drawback of most observational studies. First, Inverse Probability of Treatment Weights (IPTW) were developed and applied to all models to ensure that observable attributes were balanced across the two groups (Wooldridge 2007). Second, in addition to allowing the stochastic process to evolve over multiple clocks, and letting these components be affected by τ, all hazard models included a fixed component that was also allowed to vary across τ. Hence, this component captured any fixed differences between the treatment and control groups that are not attributable to the age-based or spell-based processes.

3.1.3. Model Implications and Effect Quantification

Let $a(t)$ and $\delta(t)$ denote the age-based and the spell-based clocks being used to measure the events. Generically, the multiple-clock stochastic process $r(t)$ may be denoted as:

$$r(t) = g\left(f_0(\tau), f_1(a(t), \tau), f_2(\delta(t), \tau)\right) \tag{3.1}$$

where, g, f_0, f_1, and f_2 are generic functions and $a(t)$ and $\delta(t)$ are the two clocks.[3]

Since the hazard is a positive quantity, its functional form can be fixed as $g(\cdot) \equiv \exp(\cdot)$. This will be derived explicitly in the next section. Lastly, one critical simplifying assumption needs to be made about how f_0, f_1, and f_2 enter $g(\cdot)$. It is assumed that the multiple-clock components enter the $g(\cdot)$ in an *additively-separable* form. Without this assumption, the specific deterrent effects and the probative effects would be difficult to isolate. These assumptions yield

$$r(t) = \exp\left(f_0(\tau) + f_1(a(t), \tau) + f_2(\delta(t), \tau)\right) \tag{3.2}$$

[3]For ease of exposition, $a(t)$ and $\delta(t)$ are left abstract here although in the application they will be specified as $a(t) = a^* + t$ and $\delta(t) = t$ where a^* is age at release and t is time since release from prison.

or

$$\log r(t) = f_0(\tau) + f_1(a(t), \tau) + f_2(\delta(t), \tau) \tag{3.3}$$

where f_0, f_1 and f_2 capture the fixed, the age-based, and the spell-based components of the hazard process respectively.

The evolution of the process with age (or spell-length) can now be captured by computing the first partial derivative of the log-hazard with respect to each component. That is:

$$\frac{\partial \log r(t)}{\partial a(t)} = f_1'(a(t), \tau) \tag{3.4}$$

$$\frac{\partial \log r(t)}{\partial \delta(t)} = f_2'(\delta(t), \tau) \tag{3.5}$$

where $\partial \log r(t) = \frac{1}{r(t)} \partial r(t)$ measures the percent change in $r(t)$. Note that the additively separable assumption implies that there are no cross-effects across the two clocks.

Next, the specific deterrent effects (SDE) and the probative effects (PRE) of DNA databases (τ) *at any point of time* can be computed as the second partial derivates of the log-hazard rates with respect to τ. That is, the SDE and PRE capture how the processes in (3.4) and (3.5) are modified by τ.

$$\text{SDE}(t) = \frac{\partial f_1'(a(t), \tau)}{\partial \tau} \tag{3.6}$$

$$\text{PRE}(t) = \frac{\partial f_2'(\delta(t), \tau)}{\partial \tau} \tag{3.7}$$

Finally, the *net* specific deterrent effect (NSDE) and the *net* probative effects (NPRE) over any horizon (e.g., the follow-up period) may be computed by integrating the above curves over the relevant domain. For example, the NSDE and

NPRE over the three-year follow-up period would be computed as:

$$\text{NSDE} = \int_0^3 \frac{\partial f_1'(a(t),\tau)}{\partial \tau} dt \tag{3.8}$$

$$\text{NPRE} = \int_0^3 \frac{\partial f_2'(\delta(t),\tau)}{\partial \tau} dt \tag{3.9}$$

where NSDE captures the percent change in recidivism events over the three-year follow-up period that is attributable to the specific deterrent effects of DNA databases and NPRE captures the percent change in the recidivism events over the three-year follow-up period that is attributable to the probative effects of DNA databases. Although not explicitly derived, the effects of unobserved differences between the treatment and control groups is explicitly allowed for in these models so that the NSDE and the NPRE are *net* of those differences.

3.2. ESTIMATION STRATEGY

In this section, an estimation strategy that will permit the estimation of parameters needed to quantify the NSDE and NPRE is described.

Assume a cohort of individuals is released from prison and followed for a period of T years. Suppose rearrest is defined as the appropriate recidivism event. If an individual is rearrested within the follow-up period T, then let b denote a binary outcome coded 1 and let d denote the duration to the first rearrest event. If the individual is not rearrested during this period, let b and d be set to 0. Now, define

$$y(t) = 1[t = d] \qquad \text{and} \qquad f(t) = 1[t \leq \min(d, T)] \qquad \forall t \in \mathscr{T}$$

where $\mathscr{T} = \mathbb{R}_+$ and $1[\cdot]$ is an indicator function returning 1 if the condition inside $[\cdot]$ is satisfied, else 0. Consequently, $y(t)$ is simply a function flagging when the event actually occurs and $f(t)$ is a function flagging when the event is at risk of occurring.[4]

Let $r(t)$ continue to denote the unknown hazard that reflects the stochastic process resulting in the event flagged by $y(t)$. Since an individual cannot fail if (s)he is not at risk of failing, both $y(t)$ and $f(t)$ can be used to derive conditional links between the hazard and the event as:

$$f(t)y(t) \approx f(t)r(t) \qquad \forall t \in \mathscr{T}. \tag{3.10}$$

Note that this approximation allows one to derive a non-parametric estimate of the hazard rate. To see this, assuming that the hazard is fixed across individuals. Then taking unconditional expectations of (3.10) and re-arranging terms yields $\hat{r}(t) = \mathbb{E}[f(t)y(t)]/\mathbb{E}[f(t)]\ \forall t \in \mathscr{T}$. This is a non-parametric estimate of the hazard rate—the number of people expected to fail at t divided by the number of people expected to be at risk of failing at t.

Besides yielding the familiar non-parametric hazard rate estimates, this approximation allows one to derive analogous links between the hazard rate and its manifestations along several clocks.

3.2.1. Specifying Distinct Processes

First, suppose that both sides of (3.10) are integrated over the domain $\mathscr{T}$ and assume that this procedure converts the approximation into an equality. Since $y(t) = 1$ if and only if $f(t) = 1$, clearly, this integration will yield the binary outcome b on the left hand side. Hence, this procedure yields the first analogy linking the hazard to a manifestation.

$$b = \int_{\mathscr{T}} f(t)r(t)dt \tag{3.11}$$

Next, consider, pre-multiplying both sides of (3.10) by t and then taking the

[4]By altering the definition of $y(t)$ and $f(t)$ one can characterize multiple events and by re-defining $f(t)$ appropriately one can characterize spells when an individual is not at risk of experiencing the event. For ease of exposition, these nuances are omitted here.

integral. The left hand side of this equation would now yield d—the duration to first rearrest (and 0 if the observation is censored)—since the only time when $f(t) = y(t) = 1$ is when $t = d$. Consequently, another analogy—linking the hazard to spell-length—would be identified.

$$d = \int_{\mathcal{T}} t f(t) r(t) dt \tag{3.12}$$

As was argued above, there may be reason to believe that the hazard of recidivism is independently affected by a stochastic process that progresses with age. Hence, the age at first rearrest event, and not just duration to first rearrest event, may be an additional manifestation to model. Multiplying both sides of (3.10) by $a^* + t$ and integrating yields this analogy linking the hazard to age at first rearrest

$$a = \int_{\mathcal{T}} [a^* + t] f(t) r(t) dt \tag{3.13}$$

because $a^* + d = a$ (age at release plus duration to first rearrest is the same as age at first rearrest). Note the functions t and $a^* + t$ were defined generically as $\delta(t)$ and $a(t)$ in the previous section.

Non-linear transformation of these outcomes can also be introduced in a parallel fashion. For example, to mimic a generalize Poisson process, one may pre-multiply and integrate both sides of (3.10) by $t \log t$ to get

$$d \log d = \int_{\mathcal{T}} t \log t f(t) r(t) dt \tag{3.14}$$

and, performing the same operation with $[a^* + t]$, to get

$$a \log a = \int_{\mathcal{T}} [a^* + t] \log[a^* + t] f(t) r(t) dt \tag{3.15}$$

In general, of course, one can derive a host of other links (with a host of other clocks). Let this set of analogous claims, say J of them, be generically written as:

$$\mu_j = \int_{\mathscr{T}} \phi_j(t) f(t) r(t) dt \qquad \forall j \in J \tag{3.16}$$

where $\phi_j(t)$ are appropriate transformation of t and μ_j are the corresponding manifestations. Provided that the analogies satisfy the basic identifying restriction—that none of them are exactly implied by, or imply, another—each of them provides information about a different piece of the model that one may be attempting to construct. In addition to the direct analogies derived above, each of them can be conditioned on the treatment indicator τ to study how τ affects the hazard process through each of the different clocks.

The analogies derived above merely provide restrictions on the shape and values that the hazard function can take. They are constraints that the final hazard model should satisfy in the sample. One still needs a way to recover information from them (i.e., convert them into parameters that can be estimated and used to test hypotheses). Fortunately, information theory provides a foundation from which to approach this problem.

3.2.2. Learning from Multiple Processes

Information theory builds on the pioneering work of Shannon (1948). He derived a measure of uncertainty—which he called *Information Entropy*—for quantifying a channel's capacity to communicate information. Faced with the problem of inferring individual features from aggregate properties, Edwin Jaynes, another pioneer in this field, proposed to use Shannon's Information Entropy as an agnostic criterion to maximize (since it measures uncertainty) in order to be very conservative in what one can (or cannot) infer from these aggregate properties (Jaynes 1957a,b). Viewing an experiment (or a sample) as a communication device, the Maximum Entropy procedure—as it has come to be known—is therefore a very general and powerful procedure for learning from statistical evidence (e.g., the type of analogies that have been derived above).

The links between Information Theory and statistics have been very thoroughly explored (Diamond 1959; Kullback 1959; Jaynes 1979, 1986, 1988; Justice 1986; Levine and Tribus 1979; Mathai 1975; Skilling 1989; Zellner 1988; Soofi 1994, 2000). Since Shannon's measure of uncertainty was probabilistic, naturally, much of this literature develops and uses measures of information based on proper probabilities. However, if one is to learn from analogies of the type defined in (3.16), what one needs is a measure of information that is based on the hazard rate.[5]

There is a growing statistical literature utilizing information theoretic concepts in reliability analysis (Ebrahimi, Habibullah and Soofi 1992; Soofi, Ebrahimi and Habibullah 1995; Ebrahimi and Kirmani 1996; Ebrahimi and Soofi 2003; Asadi et al. 2005). These scholars derive hazard models by utilizing the links between the hazard rates and probability functions (or survival rates) thereby converting the information-recovery problem about the hazard into one about proper probabilities. Unfortunately, this strategy is less than helpful in the current situation since any transformation of the derived analogies would result in intractable transformation of the manifestations themselves (μ_j). What is needed is a criterion that measures information in the hazard rate directly.

Denoting $\bar{r}(t)$ as a prior (pre-sample or pre-experiment) belief about the hazard rate, and using a simple set of plausibility assumptions, one can derive such a measure (see appendix A). Other than a constant scaling factor, the *net information acquired by the analyst* in terms of the hazard rate itself can be computed as:

$$I = \int_{\mathcal{T}} f(t)\left[r(t)\log\frac{r(t)}{\bar{r}(t)} - r(t) + \bar{r}(t)\right] dt. \tag{3.17}$$

The *inferential* task of learning from the derived constraints (the several analogies) can now be converted into the *mathematical* problem of minimizing

[5] Some measures of information relying on positive quantities (that do not integrate to 1) have been informally proposed in the literature. They are used, for example, in image reconstruction problems (Gull and Daniell 1978; Gull 1989; Donoho et al. 1992) or for recovering regression functions (Ryu 1993).

(3.17), subject to the constraints (3.16). This is a standard variational problem that can be solved by the method of lagrange. The primal objective function is set up as

$$\begin{aligned}\mathscr{L} &= \int_{\mathscr{T}} f(t)\left[r(t)\log\frac{r(t)}{\bar{r}(t)} - r(t) + \bar{r}(t)\right]dt \\ &\quad + \sum_j \beta_j\left[\mu_j - \int_{\mathscr{T}} \phi_j(t)f(t)r(t)\,dt\right]\end{aligned}$$

where β_j are the Lagrange Multipliers associated with each of the J constraints. Solving the first order conditions provides the solution

$$r(t) = \bar{r}(t)\exp\left(\sum_j \phi_j(t)\beta_j\right) \qquad \forall t \in \mathscr{T} \tag{3.18}$$

and setting $\bar{r}(t) = 1\,\forall t \in \mathscr{T}$ removes the possibility of analyst-induced subjectivity by making the priors completely uninformative.

The solution in (3.18) can be used to derive a dual representation of the optimization problem—an *un*constrained optimization problem in β_j—that can be solved using standard software with optimization routines. The dual (unconstrained) optimization problem is

$$\mathscr{F} = \sum_j \beta_j\mu_j - \int_{\mathscr{T}} f(t)r(t)\,dt + \int_{\mathscr{T}} f(t)\bar{r}(t)\,dt \tag{3.19}$$

where $r(t)$ is as derived in (3.18). Note also that since $\bar{r}(t)$ is not a function of any of the β_j, the last component of the objective function is really irrelevant in the optimization problem.

Individual attributes may be introduced into the strategy in a straightforward manner by replacing the μ_j with the products of individual manifestations and attributes (e.g., $\mu_{jn}x_{kn}$); by introducing subscripts of n (e.g., $r_n(t)$ and $f_n(t)$); and by summing the dual objective function over all individuals in the sample.

The dual objective with individual attributes included is defined as

$$\mathscr{F} = \sum_n \left\{ \sum_{kj} \beta_{kj} \mu_{jn} x_{kn} - \int_{\mathscr{T}} f_n(t) r_n(t)\, dt + \int_{\mathscr{T}} f_n(t) \bar{r}_n(t)\, dt \right\} \tag{3.20}$$

where each individual's hazard solution (path) is now defined as

$$r_n(t) = \bar{r}_n(t) \exp\Big(\sum_j \phi_{jn}(t) \sum_k x_{kn} \beta_{kj} \Big) \qquad \forall t \in \mathscr{T}. \tag{3.21}$$

The unconstrained maximization problem derived in (3.20) falls under the general class of extremum estimators, $\hat{\beta} = \arg\max_{\beta} \mathscr{F}(\beta, \mu, \mathbf{X})$. The consistency and asymptotic normality of these estimators can be established under fairly general regularity conditions (Mittelhammer, Judge, and Miller, 2000:132–139).

Assuming that standard regularity conditions are met, one can obtain an estimate of the asymptotic covariance matrix of the Lagrange Multipliers by computing the negative inverted Hessian of the dual objective function. This covariance matrix can then be used to estimate asymptotic standard errors and conduct hypothesis tests for each of the Lagrange Multipliers (β).

3.2.3. Implications

Based on the multiple-clocks that were derived earlier, this final equation can be written more specifically as:

$$\begin{aligned} \log r_n(t) &= \beta_0 + \beta_0^* \times \tau_n \\ &+ \beta_1 [a_n^* + t] + \beta_1^* [a_n^* + t] \times \tau_n \\ &+ \beta_2 [a_n^* + t] \log[a_n^* + t] + \beta_2^* [a_n^* + t] \log[a_n^* + t] \times \tau_n \\ &+ \beta_3 t + \beta_3^* t \times \tau_n \\ &+ \beta_4 t \log t + \beta_4^* t \log t \times \tau_n \end{aligned} \tag{3.22}$$

so that testing the statistical significance of $\beta_0^*, \ldots, \beta_4^*$ will help accept/reject hypothesis regarding the various multiple-clock processes. Moreover, based on this functional form, the derived NSDE and NPRE may be computed as:

$$\text{NSDE} = \int_0^3 \beta_1^* + \beta_2^*(1 + \log[a_n^* + t])\, dt \tag{3.23}$$

$$\text{NPRE} = \int_0^3 \beta_3^* + \beta_4^*(1 + \log[t])\, dt \tag{3.24}$$

Since a_n^* is different for each individual, the NDSE needs to be evaluated at some value of a^* (e.g., at the mean of the sample). The asymptotic standard errors for the NSDE and NPRE can be estimated from the asymptotic covariance matrix of the underlying β parameter using the δ-method (see Appendix A).

3.3. SUMMARY

This chapter described the identification and estimation strategy used in this research effort. Given the inherent difficulty (ethical and practical) in randomly assigning offenders to cleverly conceived treatment and comparison groups for the purpose of inferring specific deterrence and probative effects of DNA databases, this chapter developed an alternate strategy for extracting these effects from transactional data. The strategy is based on observational data.

All event history data are measured from some reference point. For the case of criminal recidivism data, several clocks are possible to define. Examples include time since birth, time since first event, time since last event, time since prison release, etc. The identification strategy used in this research effort was based on linking the two simultaneous effects of DNA databases—specific deterrence and probative—to different clocks measuring the same observed events. The age-based clock was used to identify specific deterrent effects and the spell-based clock to identify probative effects. These were motivated by the observation that any interruption in the age-based clock that can be linked to DNA databases could be construed as affecting the criminal career of an individual;

and any interruptions in the spell-based clock that could be linked to DNA databases could be construed as short-term changes in offending patterns that were net of any criminal career changes. Since the unfolding of a criminal career can most closely be associated with an individual's choices, any changes that DNA databases bring to these unfolding careers is identified as the specific deterrence effect.

Since the two clocks are different ways of measuring the same events, the multiple-clock models need to be estimated simultaneously. Moreover, a flexible functional form was considered desirable as theory provides little guidance as to the form of the trajectories other than that they are parabolic in shape. Consequently, a semi-parametric approach was devloped for estimating the models. Despite its flexibility, the framework provides a sufficiently rich apparatus to conduct hypothesis tests relating to the various processes.

The hazard of recidivism within a three year follow-up period (after release from prison) was the key outcome measure and the models linked this hazard to duration since release from prison as well as duration since birth. Each of these processes were allowed to have a parabolic shape and each of them was permitted to vary by treatment status. In addition, the hazard for the treatment and control groups was also allowed to be different without operating through either of the clocks. Hence the strategy allows DNA databases to have three distinct effects on the evolution of the hazard as time since release unfolds. First, the treatment and control groups are permitted to differ, in the aggregate, for unexplained reasons (i.e., start at different intercepts). Second, they are permitted to evolve differently as duration since release unfolds. Finally, they are permitted to evolve differently as each of the sample members age. Only those changes that affect the two dynamic processes are identified as quantities of interest. Once isolated in this manner, the specific deterrence and probative effects can be aggregated to estimate the *net* effects over the entire follow-up period.

Chapter 4

Data

4.1. DATA SOURCE

Data for this study was obtained from the Florida Department of Corrections (FDOC). As noted elsewhere, Florida's DNA databases is one of the largest in the country. Further, FDOC also maintains a very rich database for tracking offenders entering and leaving FDOC confinement and supervision. The Florida Department of Law Enforcement (FDLE) provided criminal history information. This chapter describes the sources of these data as well as the definition of the cohort, the outcomes, and the attributes of interest. It then presents descriptive and trend data on some important variables.

4.1.1. OBIS, Florida Department of Corrections

The Offender Based Information System (OBIS) maintained by the FDOC contains detailed information on all offenders who are sentenced to state prison or community supervision (probation, community control, etc.). All of the sentencing information recorded on the Sentence and Judgment Form completed by the court when an offender is convicted, including the specific offense, date of the offense and sentencing, and details as to the specific sentence is stored in this database. The OBIS also contains very specific data on all movements within and in and out of prison and all events related to community supervision outcomes (absconding, technical violations, and new offenses). There is also comprehensive data relating to the demographic characteristics of the offender; identifying numbers such as their FDLE number, social security number, and FBI number; as well as their prison experience, including disciplinary actions, programs completed, educational level, and custody classification.

The OBIS was created in 1979 and historical information on many offenders under DOC's jurisdiction was entered at that time. Also, the DOC has a unique individual identifying number for each offender, allowing one to track offenders over time in and out of the prison or community supervision systems in Florida. The OBIS also records, for each offender, whether (and a date when) the offender's DNA profile was entered into the Florida Convicted Offender database.

Since 1996, the DOC's Bureau of Research and Data Analysis has built a SAS data warehouse of over 125 research files that are extracted from OBIS and contain detailed information relating to prison and supervision admissions, releases, and status populations. Additionally, the warehouse contains event files such as prison movements, supervision gains and losses, disciplinary infractions, prison and supervision program information, etc. These files can be linked using the offender identification number and are routinely used by DOC and external researchers to build cohorts of offenders released from prison and supervision.

4.1.2. CCH, Florida Department of Law Enforcement

The Computerized Criminal History (CCH) database maintained by the Florida Department of Law Enforcement (FDLE) contains information on all arrests in Florida that result in a suspect being booked and fingerprinted at a local jail facility and is the basis of "rap sheets" used by law enforcement, the courts, and corrections to capture historical criminal history information about suspects and offenders. The CCH database was centralized at FDLE in the early 1970's, but also contains data from as far back as the 1920's.

There are four segments that make up the CCH database. First, the Identification segment includes standard demographic information and identifying numbers such as offender's social security number, FBI number, Florida's DOC number, etc. Second, the Arrest segment contains information relating to each arrest charge, such as the specific crime, data of the crime and arrest, arresting agency, county of arrest, and statutory degree of the alleged crime. Third, the Judicial segment contains information relating to the court disposition of each arrest charge (nolle prossed, pled guilty, convicted at trial, etc.), and details on the sentence received, if applicable. Fourth, the Custody segment contains information on the length of prison sentence and dates entering and exiting prison.

Arrestees are given a unique identifying number upon their first arrest in Florida; that number is used for all subsequent arrests and is used to link the information across the four segments of the CCH database for each individual.

Like DOC, FDLE's Statistical Analysis Center (SAC), has built a SAS data warehouse that contains research files of all four segments of the entire CCH database. Additionally, the SAC has been very successful in matching their CCH data to DOC's OBIS data using a host of offender identifiers, including name, date of birth, gender, race, DOC number, FDLE number, and social security number. This affords the opportunity to build a dataset for research purposes that contains comprehensive and detailed information relating to complete arrest and conviction information for all offenders who have been under the jurisdiction of DOC (prison or community supervision).

4.2. COHORT, OUTCOME, AND VARIABLE DEFINITIONS

Data obtained from the FDOC and the FDLE were combined to create an analysis file. All offenders released from FDOC between January 1996 through December 2004 were considered eligible.[1] For each individual in the cohort, crimi-

[1] Initially all offenders entering probation were also considered eligible for a seperate cohort. However, the proportion of the probation intake cohort that had DNA profiles stored in a database was very small. This cohort was subsequently dropped from the analysis.

nal history records from a matched criminal history file provided by the FDLE were obtained. A small number of sample members for whom matched criminal history records were not available were dropped from the study. Moreover, offenders not released to Florida communities (i.e., those released to other states or countries) were also excluded from the analysis as the FDLE criminal history file only contains Florida arrest records. For offenders released multiple times during the 1996-2004 period, all episodes were retained in the analysis.

Identifying the treatment and comparison group for this large cohort was somewhat tricky. Because of the evolution of Florida's DNA legislation over the study period, releasees from more recent years typically were more likely to have their DNA profiles stored—i.e., to be part of the treatment group. As a result, the same individuals could be in the treatment group and the control group. If their DNA was collected as a result of a recidivism event from an earlier release, for example, then for the initial release episode they were considered as part of the control group. If they were then convicted and received a new sentence, then for the subsequent release episode they would be treated as part of the treatment group. To ensure that the treatment and control groups reflected the then current DNA database status, the treatment group was composed of all releasees who had their DNA taken at some point prior to their release from prison. The control group was composed of all releasees who did not have their DNA entered in a database until either being rearrested or as of the end of the three-year follow-up period.

Two different outcomes were analyzed. First, the FDLE criminal history records were used to define rearrest within three years of release as an outcome. The arrest date was used to flag the recidivism event and compute duration on various clocks. Second, court docket information maintained by the FDOC was used to define a reconviction outcome, also within a three-year follow-up period. For the reconviction outcome, the offense date was used to flag the recidivism event and compute duration on various clocks. The reconviction outcome therefore flags re-offending events that ultimately led to a reconviction.

The two outcomes were not sequential linked. They were derived from two different sources and no attempt was made to reconcile the sequencing of events. They were analyzed as separate outcomes in distinct analyses.

In addition to the two outcomes of interest and the treatment indicator, a host of potentially relevant attributes were extracted and used to balance the samples. These attributes are summarized below:

TIMESERVED The total amount of time offenders had served in prison prior to their release from FDOC.

AGEREL Age at time of release from FDOC.

CHIST The criminal history measure. This includes all prior arrests (including felony and misdemeanor offenses) found in the matched arrest history file provided by FDLE.

SUPERVISION A flag identifying the supervision status of offender upon release from FDOC (whether they were to be supervised upon release).

MALE A flag identifying the gender of a releasee.

RACE_BLACK A flag identifying African American offenders (other race was the omitted category).

RACE_WHITE A flag identifying white offenders (other race was the committed category).

ETH_HISP A flag identifying offenders of Hispanic ethnicity (other ethnicity was the omitted category).

ETH_EURO A flag identifying offenders of European/Caucasian ethnicity (other ethnicity was the omitted category).

ETH_AFRI A flag identifying offenders of African ethnicity (other ethnicity was the omitted category).

ED_SCH A flag identifying high school as the highest level of education claimed (less than high school was the omitted category).

ED_COL A flag identifying some college as the highest level of education claimed (less than high school was the omitted category).

MAR_SINGLE A flag identifying single as the current marital status (other or unknown marital status was the omitted category).

MAR_MARRIED A flag identifying married as the current marital status (other or unknown marital status was the omitted category).

MAR_SEPDIVW A flag identifying separated, divorced, or widowed as the current marital status (other or unknown marital status was the omitted category).

EMP_UNEMP A flag identifying unemployed as the employment status at time of prison admission (unknown status was the omitted category).

EMP_FULL A flag identifying full-time employed as the employment status at time of prison admission (unknown status was the omitted category).

EMP_PART A flag identifying part-time employed as the employment status at time of prison admission (unknown status was the omitted category).

Finally, the most serious current offense was recovered from the FDOC data files. To recover the most serious offense, when offenders were incarcerated for more than one charge, the longest sentence length was used as a way to identify the most serious charge. Using this criteria, six offense categories were created by which to stratify the analysis. These included offenders who were released after being incarcerated primarily on Violent charges (including murder, manslaughter, sexual offenses, and other violent offenses); Robbery; Burglary; Other Property charges (including theft, fraud, and damage); Drug related charges; and Other charges (including weapons and other public order

Table 4.1: Descriptive statistics of the sample analyzed, by most serious current charge.

	Violent	Robbery	Burglary	OthProp	Drug	Other
N	30,816	11,297	20,883	26,417	37,812	14,472
UTX	0.695	0.489	0.556	0.408	0.308	0.422
RECID_ARR	0.437	0.571	0.611	0.603	0.608	0.565
RECID_CON	0.292	0.397	0.466	0.469	0.440	0.422
TIMESERVED	3.254	4.184	2.780	2.229	2.068	2.256
AGEREL	34.211	30.032	31.362	33.228	34.068	34.400
CHIST	4.334	4.906	6.387	6.686	6.785	5.965
SUPERVISION	0.468	0.437	0.628	0.694	0.784	0.712
MALE	0.919	0.945	0.960	0.864	0.873	0.936
RACE_WHITE	0.486	0.293	0.514	0.551	0.252	0.496
RACE_BLACK	0.494	0.688	0.462	0.430	0.736	0.489
ETH_HISP	0.061	0.054	0.074	0.055	0.044	0.048
ETH_EURO	0.452	0.278	0.470	0.521	0.243	0.472
ETH_AFRI	0.475	0.660	0.447	0.415	0.705	0.469
ED_SCH	0.702	0.734	0.735	0.732	0.761	0.742
ED_COL	0.059	0.043	0.041	0.063	0.044	0.048
MAR_SINGLE	0.424	0.528	0.494	0.445	0.488	0.430
MAR_MARRIED	0.138	0.099	0.093	0.125	0.107	0.134
MAR_SEPDIVW	0.175	0.095	0.124	0.166	0.127	0.165
EMP_UNEMP	0.256	0.313	0.298	0.296	0.353	0.265
EMP_FULL	0.568	0.496	0.528	0.543	0.468	0.574
EMP_PART	0.089	0.113	0.103	0.083	0.107	0.083

offenses). Table 4.1 provides the mean values for each of the variables by each of the offense categories during the study period.

4.3. UNIVARIATE TRENDS FOR KEY VARIABLES

This section discusses temporal variation in the proportion of offenders released from FDOC during the period 1996–2004 as well as the recidivism rates observed during the same periods. Based on legislation passed between these years, there were many sudden shifts in the proportion of sample members being included in the treatment group. Most of these actual “jumps” can be tied to specific legislation passed in Florida.

Figure 4.1 provides a picture of the trends in the sample of offenders released from a violent charge. Notwithstanding a few sudden shifts (notably during 2000 and 2004), the proportion of the released population that was contributing DNA to databases was increasing gradually. During 2004 legislation was passed expanding the collection of DNA evidence from a number of violent offenses (including forcible felonies, aggravated child abuse, and aggravated abuse of elder or disabled adult). At the start of the data analysis period (1996) nearly 60 percent of those released from FDOC had their DNA entered in a database. By 2004, it was nearly 95 percent.

During the same period, for this group, there was almost no change in the recidivism rates (both rearrest rates and reconviction rates). For the entire period, the rearrest rate hovered between 40 and 50 percent whereas the reconviction rate hovered about 30 percent. It was only in the last two years that one sees a small decline in the reconviction rate. Note that the recidivism events are recorded in the three years following the date of release. Hence, the recidivism events for offender released in December 2004 would have occurred between January 2005 and December 2007.

Figure 4.2 shows the same trends for those released from FDOC after serving time on robbery charges. Among this cohort, there are two distinct shifts in the proportion of offenders released from prison who have DNA recorded in a database. The first, in 2000, probably reflects offenders on robbery as well as burglary charges (as DNA collection was authorized for burglars in a 2000 legislation). The second was in 2002 when legislation specifically targeting offenders with robbery charges was enacted.

The recidivism rates of this cohort was declining gradually over the entire study period. Starting from a high of about 60 percent rearrest rate and 45 percent reconviction rate in 1996, recidivism rates dropped gradually by about 10 percent points over the next nine years. From a macro perspective, this is more persuasive of a specific deterrent effect than the trends in the violent offense category. At a minimum, increases in the proportion of offenders leaving prison with their DNA profile in a database are associated with declining rearrest rates. This graphical analysis is only suggestive, though.

Figure 4.3 shows the same trends for offenders released after serving time on primarily burglary charges. During 2000, legislation was passed authorizing the recoding of DNA profiles of all convicted burglars. This legislation yields the dramatic shift upwards in the proportion of released offenders with DNA profiles in a database from about 15 percent to nearly 100 percent within a period of a few months. No accompanying sudden shift in recidivism rates are observed, however. As with the robbery category, there is a gradual decline in the recidivism rates of this cohort over the 9-year period. The three-year rearrest rate dropped from about 65 percent to about 55 percent whereas the three-year reconviction rate dropped from about 55 percent to about 40 percent.

The next three charts, figures 4.4, 4.5, and 4.6, show the same trends for prison exit cohorts released after being incarcerated primarily for other property charges, drug charges, and other public order charges respectively. In each of these, the proportion of the release cohort that had DNA entered in a database is fairly low and stable untill 2000 when it spikes upwards. This is, more than likely, a result of offenders on multiple charges where subsidiary charges included burglary. In the case of other public order offenses, figure 4.6, there is an additional surge in 2004 that is attributable to passage of legislation authorizing the collection of DNA profiles from offenders convicted of the use and possession of firearms.

With the exception of offenders released from drug related incarcerations, the recidivism rates for other property and other public order offense cohorts remained fairly stable through the study period. The recidivism rates of the drug cohort dropped continuously throughout the period. The rearrest rate dropped from nearly 70 percent in 1996 to about 55 percent in 2004. Similarly, the reconviction rate dropped from 50 percent in 1996 to about 35 percent in 2004.

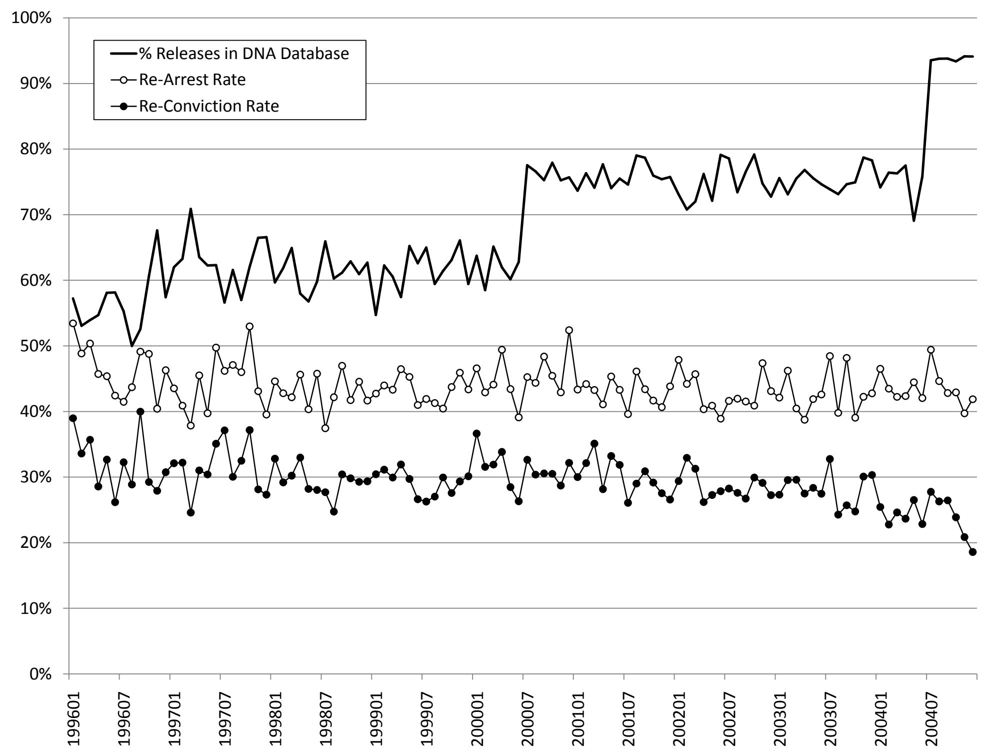

Figure 4.1: Proportion of prison releasees who had DNA evidence in a database and recidivism rates, current offense: Violent, 1996–2004.

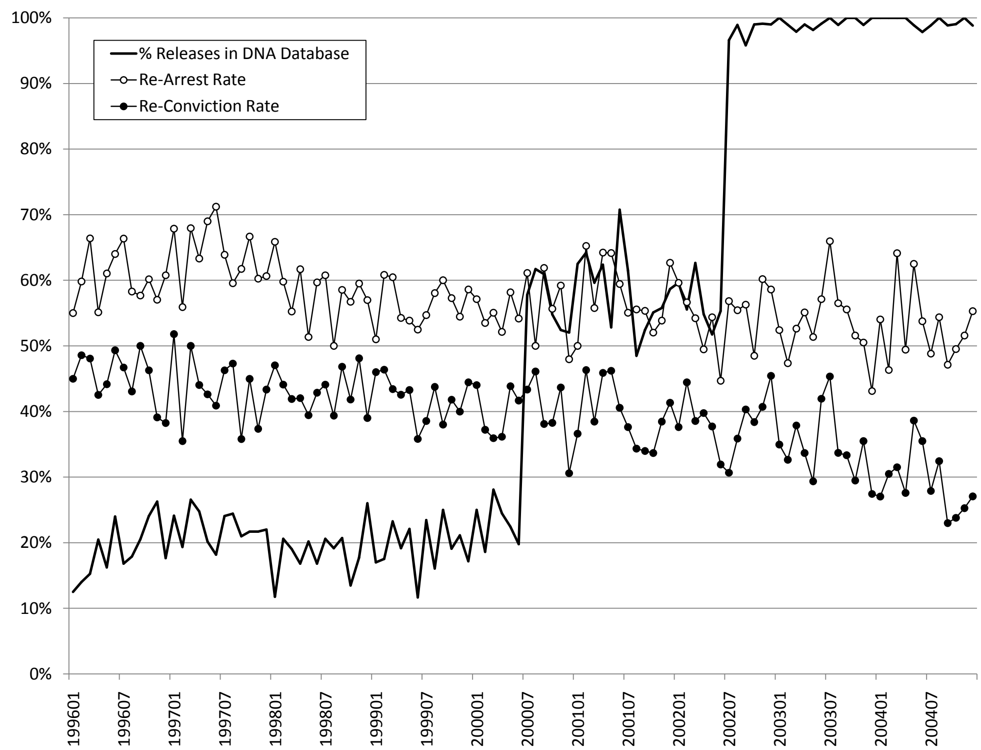

Figure 4.2: Proportion of prison releasees who had DNA evidence in a database and recidivism rates, current offense: Robbery, 1996–2004.

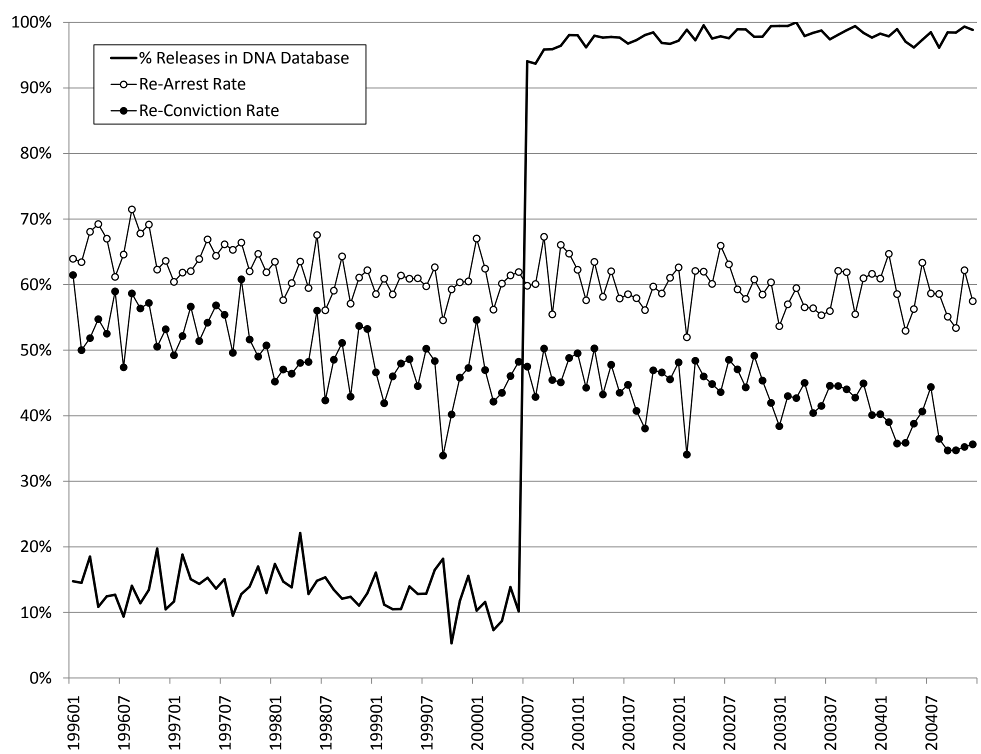

Figure 4.3: Proportion of prison releasees who had DNA evidence in a database and recidivism rates, current offense: Burglary, 1996–2004.

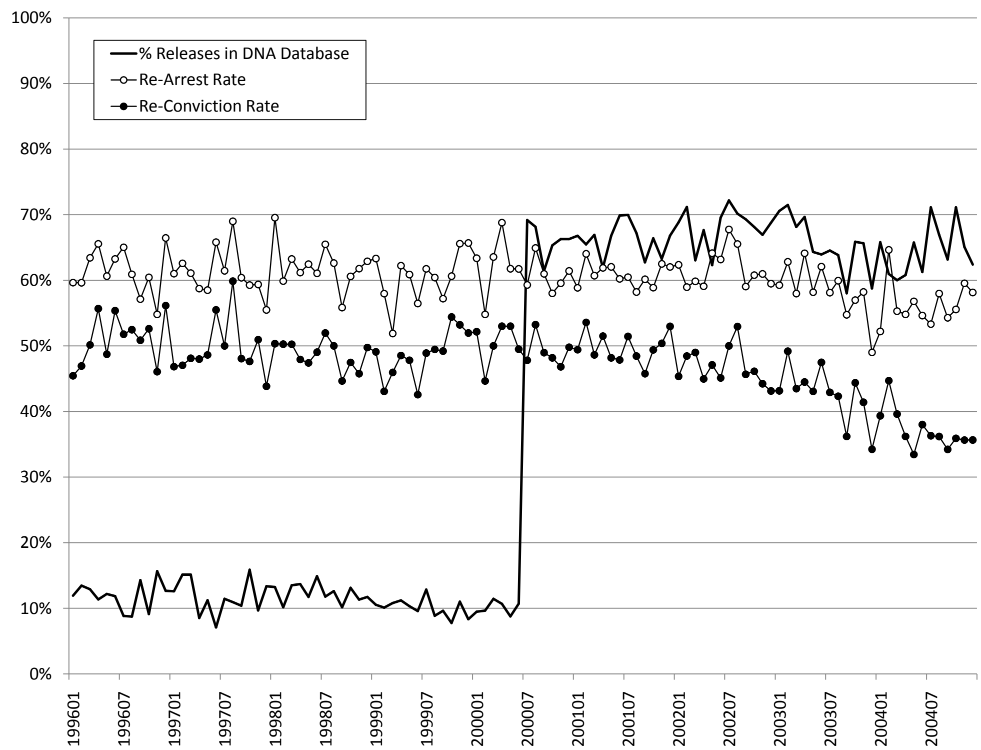

Figure 4.4: Proportion of prison releasees who had DNA evidence in a database and recidivism rates, current offense: Other property, 1996–2004.

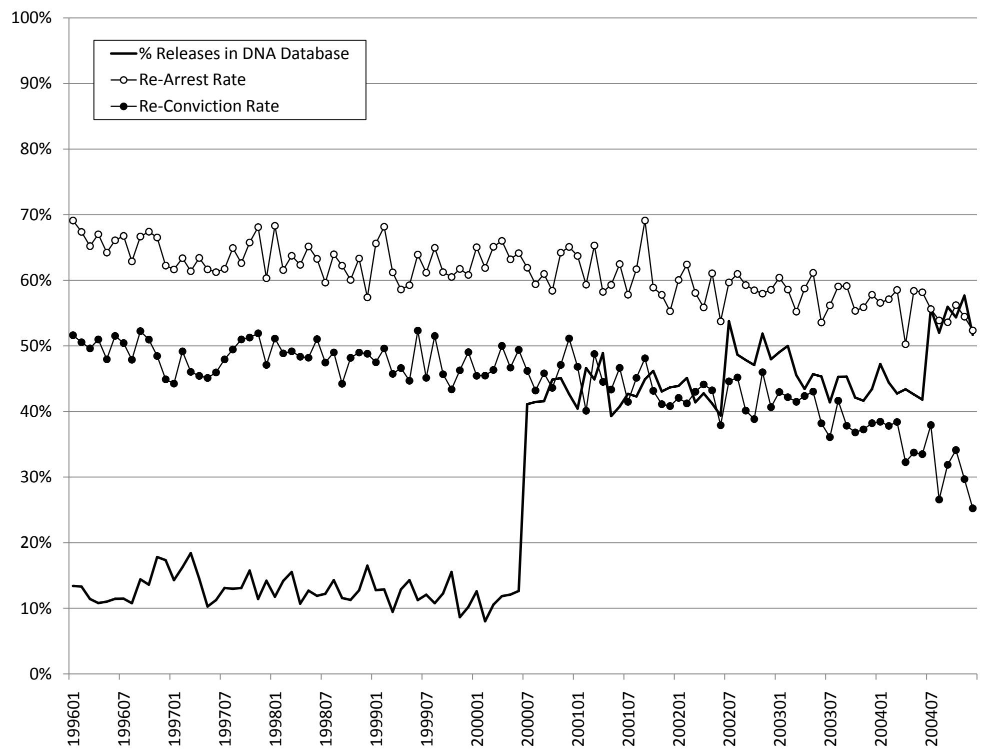

Figure 4.5: Proportion of prison releasees who had DNA evidence in a database and recidivism rates, current offense: Drug, 1996–2004.

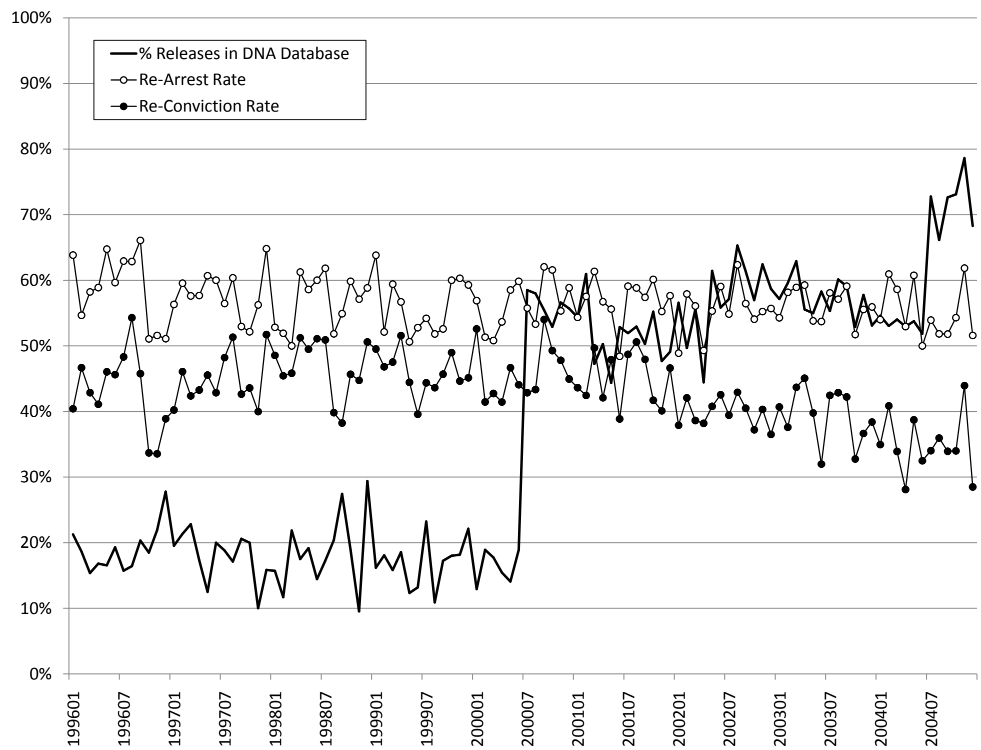

Figure 4.6: Proportion of prison releasees who had DNA evidence in a database and recidivism rates, current offense: Other, 1996–2004.

Chapter 5

Findings

This chapter presents and discusses main findings. The chapter is organized as follows. The models used to create the IPTW (inverse probability of treatment weights) in order to balance the samples are first discussed. Pre- and post-balancing comparisons of the characteristics are provided. Results of the multiple-clock models estimated to recover the deterrent and probative effects of DNA databases are provided and discussed next. Finally, the implied NSDE and the NPRE estimates are presented.

5.1. INVERSE PROBABILITY OF TREATMENT WEIGHTS (IPTW)

Since interest centers around the estimation of conditional multiple-clock models with just the treatment dummy τ included, the first step in the analysis was to assess the extent to which the attributes of the two groups differed. If they did, then Inverse Probability of Treatment weights were used to balance the samples (Wooldridge 2007). To do so, logistic regression models were estimated (for each offense category and outcome type) that predicted the probability of each sample unit having DNA evidence in a database prior to release. Available attributes included time served prior to release, age at release, criminal history (total number of prior arrests), supervision status at release, gender, race, ethnicity, highest education level attained, and employment status (prior to incarceration). Detailed model estimates are provided in Appendix B. Let $p_n(\tau)$ denote the estimated probability (propensity) that individual n was in the treatment group. The inverse probability of treatment weights were computed as:

$$w_n = \tau_n \times \frac{1}{p_n(\tau)} + (1 - \tau_n) \times \frac{1}{1 - p_n(\tau)} \tag{5.1}$$

and normalized appropriately to ensure that the weighted and unweighted sample sizes were identical. Tables 5.1 and 5.2 provide detailed comparisons of the attributes of the treated and the untreated groups—with and without the IPT weights.

There are 6 columns for each of the offense categories displayed in these tables. The first two columns under any offense category provide the unweighted means of each of the attributes included. The third column provides the statistical significance of the difference between the two groups. Significant differences are indicated with stars—two stars for 95 percent confidence and a single star for 90 percent confidence. Note because of rounding, some differences appear to be small when in fact they are statistically significant. The next three columns provide the same comparison using the IPTW to weight the data.

In almost all of the models, the weighting makes the differences insignificant. There are a few notable exceptions. In the violent and the other offense models, the time served variable could not be balanced. Similarly, in the drugs model the criminal history variable could not be balanced. However, some of the remaining differences are very small despite being statistically significant.

In order for propensity scores to provide an appropriate basis for creating weights, there are two critical assumptions that need to be satisfied (Wooldridge 2007). First, there needs to be sufficient overlap in the range of estimated propensity scores in the treatment and the comparison groups. To assess the overlap, figure 5.1 shows the distribution of the estimated propensity scores across the six offense categories considered. The gray bars represent the distribution of the

Table 5.1: Unweighted and weighted samples compared, current charge: Violent, Robbery, and Burglary.

	Current Charge = Violent						Current Charge = Robbery						Current Charge = Burglary					
	Unweighted			IPT Weighted			Unweighted			IPT Weighted			Unweighted			IPT Weighted		
	tx=0	tx=1		tx=0	tx=1		tx=0	tx=1		tx=0	tx=1		tx=0	tx=1		tx=0	tx=1	
TIMESERVED	2.20	3.75	**	4.64	3.03	**	3.73	4.66	**	4.24	4.19		2.62	2.91	**	2.76	2.77	
AGEREL	32.61	35.10	**	34.99	33.80		29.25	30.85	**	30.07	30.05		30.80	31.81	**	31.34	31.34	
CHIST	4.36	4.32	**	4.41	4.39		4.66	5.16	**	4.95	4.94		6.31	6.45		6.40	6.40	
SUPERVISION	0.56	0.43	**	0.48	0.49		0.45	0.42		0.44	0.44		0.65	0.61	**	0.63	0.63	
MALE	0.89	0.94	**	0.92	0.91		0.94	0.95		0.94	0.94		0.96	0.96	**	0.96	0.96	
RACE_WHITE	0.50	0.49		0.47	0.49		0.28	0.31		0.29	0.29		0.50	0.52		0.51	0.51	
RACE_BLACK	0.48	0.49		0.51	0.49		0.70	0.67	**	0.69	0.69		0.48	0.45	**	0.46	0.46	
ETH_HISP	0.06	0.06	*	0.06	0.06		0.05	0.06		0.05	0.05		0.06	0.08		0.07	0.07	
ETH_EURO	0.46	0.45		0.44	0.45		0.27	0.28		0.28	0.28		0.47	0.47		0.47	0.47	
ETH_AFRI	0.47	0.47		0.49	0.48		0.67	0.65		0.66	0.66		0.46	0.44		0.45	0.45	
ED_SCH	0.70	0.69	*	0.69	0.70		0.73	0.74	**	0.73	0.73		0.71	0.75	**	0.73	0.74	
ED_COL	0.06	0.06		0.08	0.06	**	0.04	0.04		0.04	0.04		0.04	0.04		0.04	0.04	
MAR_SINGLE	0.41	0.43		0.43	0.42		0.53	0.53	**	0.53	0.53		0.53	0.47	**	0.49	0.49	
MAR_MARRIED	0.12	0.15	**	0.14	0.14		0.10	0.10	**	0.10	0.10		0.10	0.09	**	0.09	0.09	
MAR_SEPDIVW	0.16	0.18		0.18	0.17		0.10	0.09	**	0.09	0.09		0.14	0.11	**	0.12	0.12	
EMP_UNEMP	0.27	0.25		0.27	0.26		0.30	0.33	**	0.31	0.31		0.30	0.30	*	0.30	0.30	
EMP_FULL	0.56	0.58		0.56	0.57		0.51	0.48		0.50	0.50		0.52	0.53	**	0.53	0.53	
EMP_PART	0.09	0.08		0.10	0.09		0.11	0.12	**	0.11	0.11		0.10	0.10		0.10	0.10	

Table 5.2: Unweighted and weighted samples compared, current charge: Other Property, Drugs, and Other.

	Current Charge = OthProp						Current Charge = Drug						Current Charge = Other					
	Unweighted			IPT Weighted			Unweighted			IPT Weighted			Unweighted			IPT Weighted		
	tx=0	tx=1		tx=0	tx=1		tx=0	tx=1		tx=0	tx=1		tx=0	tx=1		tx=0	tx=1	
TIMESERVED	2.04	2.50	**	2.24	2.24		1.91	2.41	**	2.07	2.09		1.85	2.81	**	2.50	2.32	**
AGEREL	33.10	33.41		33.27	33.23		33.58	35.16	**	34.09	34.08		33.99	34.96	*	34.49	34.36	
CHIST	6.16	7.45	**	6.80	6.82		6.17	8.18	**	6.89	6.97	**	5.29	6.88	**	6.09	6.07	
SUPERVISION	0.73	0.65	**	0.69	0.69		0.80	0.74	**	0.78	0.78		0.74	0.68	**	0.71	0.71	
MALE	0.82	0.93	**	0.86	0.87		0.85	0.93	**	0.87	0.88		0.91	0.96	**	0.94	0.94	
RACE_WHITE	0.55	0.55		0.55	0.54		0.26	0.24		0.25	0.24		0.50	0.49		0.49	0.49	
RACE_BLACK	0.43	0.43	**	0.43	0.44		0.73	0.74	**	0.74	0.75		0.48	0.50		0.49	0.50	
ETH_HISP	0.05	0.06		0.05	0.05		0.04	0.04		0.04	0.04		0.04	0.06	**	0.05	0.05	
ETH_EURO	0.53	0.51		0.52	0.52		0.25	0.23		0.24	0.24		0.48	0.46		0.47	0.47	
ETH_AFRI	0.41	0.42		0.42	0.42		0.70	0.72	*	0.71	0.71		0.46	0.48		0.47	0.48	
ED_SCH	0.72	0.75	**	0.73	0.73		0.76	0.77	**	0.76	0.76		0.75	0.74		0.74	0.74	
ED_COL	0.07	0.05	**	0.06	0.06		0.05	0.04	**	0.04	0.04		0.05	0.04	**	0.05	0.05	
MAR_SINGLE	0.43	0.46	**	0.45	0.45		0.47	0.54	**	0.49	0.49		0.41	0.46		0.43	0.43	
MAR_MARRIED	0.13	0.11	**	0.12	0.12		0.11	0.10	*	0.11	0.11		0.13	0.14		0.13	0.13	
MAR_SEPDIVW	0.18	0.14	**	0.17	0.16		0.13	0.12	**	0.13	0.13		0.17	0.16	*	0.17	0.16	
EMP_UNEMP	0.30	0.30	**	0.30	0.30		0.36	0.35	**	0.35	0.36		0.27	0.26	**	0.26	0.27	
EMP_FULL	0.54	0.55	**	0.54	0.54		0.46	0.49	**	0.47	0.47		0.57	0.58	**	0.57	0.57	
EMP_PART	0.08	0.09	**	0.08	0.08		0.11	0.10		0.11	0.11		0.08	0.08	**	0.08	0.08	

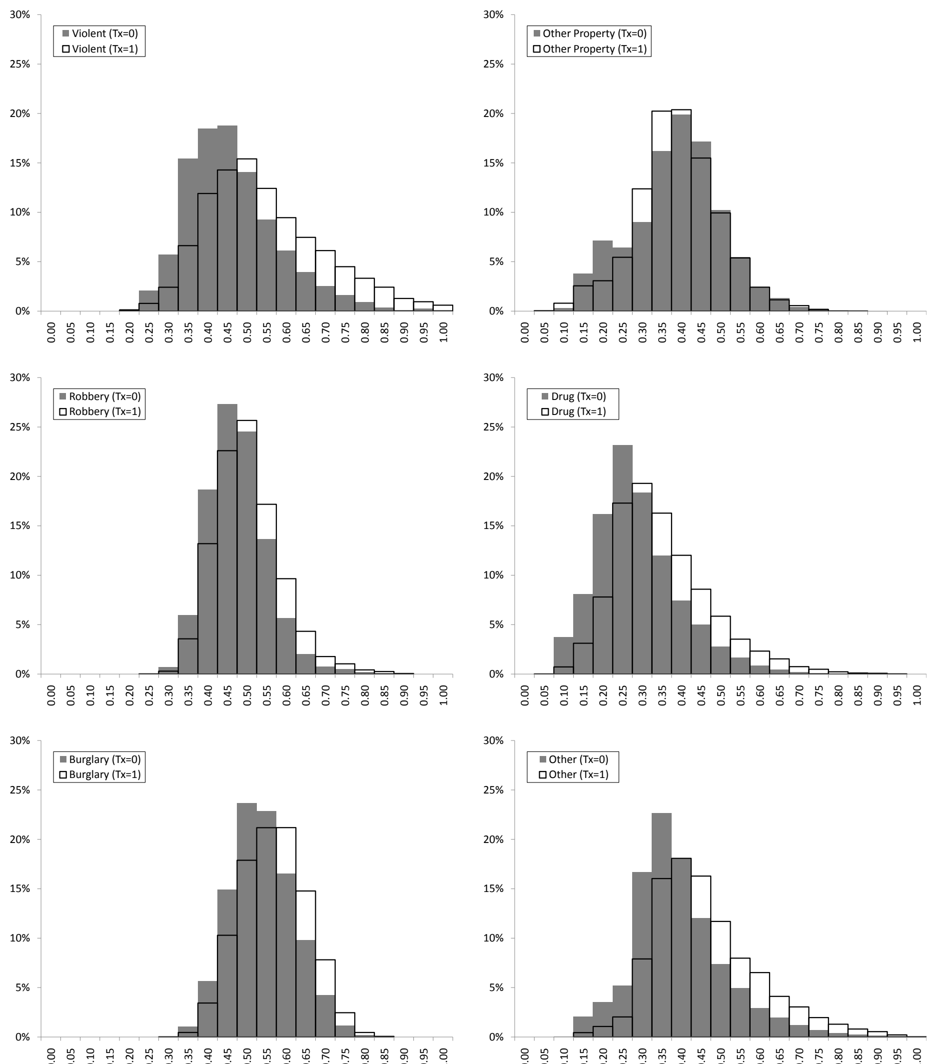

Figure 5.1: Propensity score overlap in offense specific models.

estimated propensity score in the control group ($\tau = 0$) and the hollow outlined bars represent the distribution of the propensity scores in the treatment group ($\tau = 1$). The overlap seems adequate.

A second assumption concerns the actual value of the estimated propensity score. Since weights need to be created by inverting the scores, propensity scores in the treatment group need to be away from 0 (otherwise the inverse will create a very large weight) and scores in the control group need to be away from 1 (otherwise the inverse of one minus the score will create a very large weight). Based on the distributions displayed in figure 5.1, with the exception of violent offense category models, this assumption seems to generally be satisfied. Despite that, in all models, the normalized weight was top-coded to a value of 4 (all weights larger than 4 were set to 4). This ensures that none of the raw observations contribute to more than 4 weighted observations in any of the ensuing analysis.

Is the IPTW methodology appropriate to use in the current context? In a recent critique of the methodology, Bjerk (2009) showed that the IPTW methodology and, more generally, fixed effects models can yield misleading inference in the presence of *dynamic selection bias*.[1] Bjerk (2009) summarizes the critique as follows:

> "In general, fixed-effects type estimators can only provide an unbiased estimate of the causal effect of some individual characteristic x on individual criminality if one can truly believe that the reason individuals obtain that characteristic x at a given point in time is because an opportunity for obtaining that characteristic randomly arose at a given point in time that was not available previously. If, on the other hand, the opportunity for some individuals to obtain characteristic x was always there to some extent, and it is simply that something changed within or around the individual that causes him to choose to act on the opportunity to obtain characteristic x at a given point of time, then estimated fixed-effects relationships

[1] I thank an anonymous reviewer for raising this point.

will likely overstate the causal effect of characteristic x on individual criminality " [394]

As it relates to this report, the individual characteristic x that Bjerk (2009) is referring to is the treatment indicator τ—having one's DNA entered into a DNA database prior to release from prison. Since the passage of laws in the state of Florida are largely *exogenous* to an individual's choices, it is difficult to conceptualize how the individual could have had the opportunity to obtain τ prior to the passage of the law. Additionally, although not random, the opportunity to obtain τ arose exogenously for the individual. Nothing changed within an individual for the individual to choose to acquire τ. Hence, it is unlikely, in the opinion of this author, that dynamic selection bias will reduce the utility of the IPTW methodology in the context of the current research effort.

5.2. MODEL ESTIMATES

Table 5.3 provides a summary of the main multiple clock models. All models were weighted using the IPT weights discussed in the last section. This table summarizes the sign and significance of the parameters identified in (3.22).[2] With rearrest or reconviction as the outcome of interest, there is clear evidence in most offense categories that there are multiple processes operating simultaneously. Moreover, it is evident that having one's DNA profile recorded in a database (τ) does affect these processes in distinct and interesting ways. A brief explanation of the parameter values follows.

The first set of parameters β_0 and β_0^* related to the fixed (non-temporal) part of the hazard process (f_0). Here it is interesting to note that despite balancing the data on almost all of the attributes, the treatment group has a higher hazard than the untreated group (that is not associated with either of the clocks). This is indicated by the positive and statistically significant coefficients on β_0^* in most of

[2] Two pluses (minuses) implies a positive (negative) coefficient with a p-value of less than or equal to 0.05; a single plus (minus) indicates a positive (negative) coefficient with a p-valules of less than or equal to 0.1. A zero idicates a statistically insignificant coefficient.

Table 5.3: Parameter estimates (sign and statistical significance), multiple-clock models, all offense types.

Component	β's	Violent	Robbery	Burglary	OthProp	Drug	Other
				Rearrest Models			
1	β_0	−−	−−	−−	−−	−−	−−
τ	β_0^*	++	++	++	++	0	0
a	β_1	++	+	++	++	−−	0
$a \times \tau$	β_1^*	−−	−−	−−	−−	0	0
$a \log a$	β_2	−−	−−	−−	−−	0	0
$a \log a \times \tau$	β_2^*	++	+	++	++	0	0
t	β_3	0	−−	−−	−−	−−	−−
$t \times \tau$	β_3^*	−−	0	++	+	++	++
$t \log t$	β_4	−−	−−	0	0	−−	0
$t \log t \times \tau$	β_4^*	++	0	0	0	−	0
				Re-conviction Models			
1	β_0	−−	−−	−−	−−	−−	−−
τ	β_0^*	0	++	++	++	0	0
a	β_1	++	++	++	++	0	0
$a \times \tau$	β_1^*	0	−−	−−	−−	0	0
$a \log a$	β_2	−−	−−	−−	−−	0	0
$a \log a \times \tau$	β_2^*	0	++	++	++	0	0
t	β_3	−	−−	−−	−−	−−	−−
$t \times \tau$	β_3^*	0	0	++	0	++	++
$t \log t$	β_4	−−	0	0	0	0	0
$t \log t \times \tau$	β_4^*	0	0	−−	0	−−	−−

$++(\beta > 0, p \leq 0.05)$; $+(\beta > 0, p \leq 0.10)$; $--(\beta < 0, p \leq 0.05)$; $-(\beta < 0, p \leq 0.10)$; $0(p > 0.1)$.

the model. The exceptions are Drug and Other offense categories in the rearrest and the reconviction models and, additionally, the Violent offense category in the reconviction models.

The parameters β_1 and β_2 capture how the hazard unfolds with age—the age-based clock. In most of the models, β_1 is positive and β_2 is negative. This indicates a process that increases with age at a decreasing rate. This shape is consistent with the traditional age-crime curve. The β_1^* and β_2^* coefficients, on the other hand, reflect how treatment affects the age-based process. In most of the models, these coefficients take on signs opposite to the age-crime curve suggesting that treatment slows down the process. This is what one would expect if a specific deterrent effect actually existed. That is, offenders who have their DNA recorded in a database are on a lower hazard path than those in the control group. However, the actual values of the SDE and the NSDE are dependent on the data points at which they are evaluated. More on this later.

The probative effect is computed from the spell-based clock. The β_3 and β_4 parameters reflect this second process. Here, one finds that the parameters are typically negative (or 0). Hence, either the spell-based process decreases at a constant rate or decreases at a decreasing rate. In either case, the spell-based process is decreasing in intensity. The β_3^* and β_4^* parameters now reflect the effects of treatment on this spell-based process—capturing the probative effects of DNA databases. Here one finds that β_3^* is typically positive when it is significant indicating that treatment slows down the decaying process. This means, treatment actually increases the hazard rate compared to non-treatment. This is the probative effect of DNA databases. Offenders who have their DNA recorded in a database are likely to be rearrested and reconvicted quicker than the control group.

5.3. IMPLIED DETERRENT AND PROBATIVE EFFECTS

The net specific deterrent and probative effects, as derived in (3.23) and (3.24) respectively, implied by the estimated parameters summarized in table 5.3 are presented in table 5.4 and discussed next. These effects are computed at the mean age at release for each of the offense specific samples. Also, they are integrated over the three year follow-up period.

Since the computations are based on the log-transformed hazard rate, each of them represents a percent change. For example, a NSDE of -0.05 implies a 5 percent reduction in the recidivism events over the follow-up period that is attributable to specific deterrence. Similarly, a NPRE of 0.05 implies a 5 percent

Table 5.4: Implied net specific deterrent effects (NSDE) and net probative effects (NPRE) of DNA databases.

	Violent	Robbery	Burglary	OtherP	Drug	Other
Rearrest Models						
NSDE (3 year)	0.012*	-0.029**	-0.025**	0.021**	-0.004	0.017**
NPRE (3 year)	0.276**	0.308**	0.387**	0.337**	0.403**	0.124
Re-conviction Models						
NSDE (3 year)	0.001	-0.032**	-0.028**	0.020**	-0.005	0.001
NPRE (3 year)	0.182*	0.071	0.078	0.243**	0.271**	0.028

$^{**}p \leq 0.05$; $^{*}p \leq 0.10$

increase in recidivism events over the follow-up period that is attributable to the probative effects of DNA databases.

For the rearrest models, the NSDE findings are mixed and offense-category specific. For all of the models, the NSDE is in the one to three percent range. However, three of the models produce net *increases* in recidivism events—contrary to a specific deterrence hypothesis. These include violent, other property, and the other categories. It is comforting, however, to see that for burglary and robbery—the types of crimes for which biological evidence is easy to obtain—the effects are negative and consistent across both outcomes. The findings are similar but somewhat more encouraging for the reconviction models. Here, the NSDE effects for robbery and burglary continue to remain negative and statistically significant. The positive NSDE effects (contrary to the specific deterrence hypothesis) for violent and other crime categories are no longer significant, though.

The probative effects largely comport to expectations. All effects across the two outcomes are positive. With the exception of the other crime category, the rearrest models produce NPRE effects in the 30 to 40 percent range. Moreover, with the exception of the other crime category, all of the effects were found to be statistically significant. Findings are less consistent for the reconviction models. Typically, the probative effects as computed from the rearrest models are larger in magnitude than those computed from the reconviction models. Surprisingly, the NPRE were not statistically significant for the robbery and burglary models.

Four aspects of these results are worth elaborating on. First, in some instances, the NDES and NPRE models take on the same sign across two or more models when the underlying β parameter signs are different. For example, the NPRE from all rearrest models are positive despite the fact that β_3^* and β_4^* parameters for various crime cateories taking on different signs. This is entirely plausible. Recall that the NSDE and the NPRE are computed as integrals over the follow-up period. As such, they reflect the area under a curve (the subtrajectories). The underlying β parameters reflect the slopes of these curves. Upward sloping and downward sloping curves can both have positive areas under them over the follow-up period.

Second, the strongest and most consistent findings regarding the NSDE emerge for the robbery and burglary rearrest models. One reason why that might be is that robbery and burglary are the types of crimes for which biological evidence is relatively easier to obtain. Another reason why these effects may be particularly strong is that the passage of legislation in Florida clearly demarcated the treatment and control regimes. Of all the crime categories considered, the sharpest and most complete coverage relate to robbery and burglary. For example, figure 4.2 shows that the proportion of offenders released from prison who had DNA evidence stored in a database went from about 20 percent to 60 percent in July 2000, and then from 60 percent to nearly 100 percent in July 2002. Thereafter it remained at or about 100 percent. Similarly, figure 4.3 shows that that proportion of offenders released from prison who had DNA evidence entered in searchable databases rose from 15 percent to about 95 percent in July 2000, and has remained near 100 percent ever since then. Although other crime categories show similar increases tied to passage of legislation, the demarcation is not so clear and complete.

Third, although the signs of the NSDE and NPRE are always consistent across the two outcomes, the size of the effects and inference about them are not always similar. For example, the size of the NPRE for robbery and burglary drops by a factor of 4 between the rearrest and the re-conviciton model and the effects are not significant in the reconviction models (although they continue to have the same signs). Given that reconviction usually takes longer than rearrest, reconvictions are more rare in the data. As such, it is possible that the different base rates in the samples have an effect on the inconsistencies. However, this is an anomaly that deserves further scrutiny.

Fourth, the only other study where comparable estimates have been reported appears to be the U.K. Home Office sponsored evaluation (Home Office 2004). Interestingly enough, their reported probative effects are in the 19 to 20 percent range whereas a 1 percent reduction of crime was realized in the target area. The findings reported in this study are on the same scale. However, it is important to note that the specific deterrent effects from this study are somewhat larger but are computed as reduction in recidivism not general crime.

These findings and their implications are further summarized in the next chapter.

Chapter 6

Conclusion

6.1. SUMMARY

The main goal of this research effort was to quantify the specific deterrent effects of DNA databases. All states in the United States currently require some categories of convicted offenders to submit biological samples for DNA analysis. Profiles extracted from these samples are stored in a searchable database that aids law enforcement authorities in solving crimes, prosecuting suspects, and in exonerating the wrongfully convicted. The general trend among state legislatures is to expand the coverage of these databases. More crime categories are included by legislation and more funds have been made available to clear backlogs. Are there benefits to be accrued from this massive investment?

There is no doubt that forensic evidence, particularly DNA profiles, have huge probative value. Conviction of guilty offender because of DNA evidence, identification of suspects because of solved "cold cases," and exoneration of the wrongfully convicted are well documented benefits of this trend. Given the near certainty with which DNA identifies and places suspects near the scene of a crime, might these benefits not deter offenders who know that their DNA profile exists in a searchable database? Indeed, legislation sometimes explicitly identifies specific deterrence as a reason for expanding the coverage of these

DNA profile databases (Taylor et al. 2007). Deterrence theory certainly suggest that specific deterrent effects should materialize. Owing to its demonstrated probative value, it is plausible to believe that offenders are keenly aware that DNA evidence assists tremendously in solving crimes and in prosecuting suspects. The swiftness and the certainty of punishment is clearly many fold when DNA matched evidence is utilized. Therefore, knowledge about the fact that one's DNA profile exists in a database to be conveniently searched at a later date should deter these offenders (at least on the margin). Hence, specific deterrence effects are very plausible.

This study utilized a large cohort of offenders released from Florida Department of Corrections between 1996 and 2004 to test this hypothesis. Given that the study relied exclusively on observational data, the simultaneous nature of the specific deterrence effects, probative effects, and the effects of unbalanced attributes—observed or unobserved—needed to be identified distinctly. This study relied on multiple-clock models to identify the three distinct processes.

Multiple clock models provide a convenient means of measuring the same event on multiple clocks, and then modeling these processes distinctly. If a reasonable case can be made for linking different theoretical claims to the different clocks, then it is possible to use these models to identify the distinct effects. This study linked the specific deterrent effects to the age-based clock, the probative effects to the spell-based clock, and the residual (unexplained) effects to a fixed non-temporal component. The analysis shed some light on the various hypotheses considered.

First, there is evidence of the specific deterrence effect. Findings were particularly interesting for robbery and burglary. They were both in the expected direction—negative effects implying a deterrence effect—and were based on computations using statistically significant parameter estimates.

Second, there was even stronger evidence for the probative effects. Findings show that most of the computed probative effects were in the expected direction—positive effects implying increased recidivism—and were fairly large.

Third, some of the specific deterrence effects recovered were perversely signed. That is, the net effects of DNA databases that is attributable to specific deterrence was actually positive. The probative effects were pretty consistently in the correct direction.

Fourth, where they were in the correct direction and statistically significant, the specific deterrence effects and the probative effects were of a magnitude very similar to findings reported by the U.K. Home Office (Home Office 2004). Specific deterrence effects were in the range of 2 to 3 percent (the Home Office study documented roughly 1 percent) and the probative effects ranged in the 20 to 30 percent range (the Home Office study documented about 20 percent.

6.1.1. Limitation

All non-experimental studies are sub-optimal compared to experiments. However, they are typically cheaper and can be used to provide some guidance to policy makers. Moreover, sometimes analysis can be conducted using readily available transactional datasets. To the extent that experiments can be conducted to confirm or reject the general findings from this study, they would be valuable to conduct.

The data used for this study contain a finite number of attributes that could be extracted and balanced on. As with all matching or weighting estimators, the crucial *unconfoundedness* assumption must be maintained. That is, it is implicitly assumed that once all the available attributes are balanced on, the treatment and control groups are no longer unbalanced on relevant (or crucial) attributes thereby permitting causal interpretations (Rubin 1990). This is typically an unverifiable assumption. Only well conducted experiments can guarantee that the treatment and control groups are balanced on all observed and unobserved attributes.

Moreover, given the nature of the intervention (DNA legislature) that covers everyone eligible, the treatment and control groups come from different time periods. Hence, implicitly, the comparisons of the hazard paths are between offenders released in more recent years (the treatment group) to offenders released in past years (the control group). Although attempts were made to balance the samples on all available attributes, all aspects of the judicial environment are probably not balanced. For that reason, fixed effects for the two groups were permitted. That is, the NSDE and the NPRE effects are net of any fixed differences between the two groups. Despite this possibility, one cannot rule out that there may have existed other policy trends that coincided with the passage of the DNA legislation. One possibility for future research is to assess if DNA legislation was adhered to more/less strictly in different parts of the state and assess these differences while controlling for other common justice policies. Applying the multiple-clock framework utilizing knowledge of such natural experiments may provide clearer insights.

6.2. IMPLICATIONS FOR POLICY AND PRACTICE

Do DNA databases provide indirect benefits like deterring convicted offenders from committing future crimes? Should state legislatures continue to expand coverage of DNA databases?

The answer to the former question, based on this study, is mixed. Perhaps for some types of crimes there are stronger deterrent effects than others. Clearly, property crimes like robbery and burglary show deterrence effects. There is nearly a 2 to 3 percent reduction in recidivism events over the follow-up period that can be attributed to specific deterrence. But is that sufficient? This research was not designed to address this latter question. It is safe to say, however, that if at all the expansion is to continue, it should be focused on property related crimes like burglary or robbery. Moreover, such crimes are usually the scenes where high volumes of biological evidence may be collected.

On the other hand, one can argue that the specific deterrent effects uncovered in this study are too small to warrant serious attention. Why are the effects so small? Taylor et al (2007) make a convincing case that overwhelming the system may indeed have the perverse effect of diminishing whatever specific deterrence effects may have existed. However, these negative effects must be placed in the correct context. If, as was uncovered in this study and in the U.K. Home Office study, the specific deterrence effects are small, then sacrificing these effects for the huge probative benefits that research has clearly demonstrated time and again, may be well worth it. There is, after all, no theoretical claim that recording an individual's DNA profile in a database has any *criminogenic* effects on the individual. As such, the trade-off is clearly in favor of future expansion of the realm of crimes and category of offenders covered by DNA databases.

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Appendix A

Mathematical Appendix

A.1. DERIVING THE INFORMATION CRITERION

Since a key component of the procedure for learning from multiple processes outlined in the narrative was the functional form of the information criterion (3.17), this appendix provides a brief derivation of this measure based on a minimal set of plausible assumptions.

Let the information acquired about a counting process *at time t* be some function of the divergence between the prior (pre-sample or pre-experiment) assessment of the hazard, $\bar{r}(t)$, and its posterior (post-analysis or post-experiment) assessment, $r(t)$. Let us denote this quantity as $I(t) = f(r(t), \bar{r}(t))$. What is reasonable to assume about this function? In other words, what are reasonable properties for the function f to possess?

The first set of assumptions pertain to the range of values information can take. Keeping in mind that all quantities are indexed by t (i.e., we are talking about information at a particular t), let

$$f \geq 0 \qquad \forall r, \bar{r} > 0 \tag{A.1a}$$

$$f = 0 \qquad \forall r = \bar{r} \tag{A.1b}$$

Here, (A.1a) states that information is a non-negative quantity for all values of the prior and posterior hazard rates and (A.1b) states that if the posterior is exactly the same as the prior, then no information has been acquired.

The second set of assumptions deal with how information changes as the absolute value of the posterior increases. Let

$$\frac{df}{dr} > 0 \qquad \forall r > \bar{r} \tag{A.2a}$$

$$\frac{df}{dr} < 0 \qquad \forall r < \bar{r} \tag{A.2b}$$

$$\frac{df}{dr} = 0 \qquad \forall r = \bar{r} \tag{A.2c}$$

These assumptions simply state that the amount of information increases if the posterior moves further away from the prior—whether or not r is higher or lower than $\bar{r}$. For example, (A.2a) implies that if $r > \bar{r}$ then an increase in r adds to information since it takes the analyst further away from the prior. Similarly, (A.2b) implies that if $r < \bar{r}$ then an increase in r brings the analyst closer to the prior. (A.2c) implies that f is continuous in r.

The last set of assumptions deal with the notion of diminishing marginal returns. The idea is that the same increase in the posterior hazard should imply smaller informational gains if the hazard is already high, compared to if the hazard were low. This assumptions translates to

$$\left.\frac{df}{dr}\right|_{r=r_1} > \left.\frac{df}{dr}\right|_{r=r_2} \qquad \forall r_1 < r_2 \tag{A.3a}$$

or, put another way, it translates to the second order differential equation

$$\frac{d^2 f}{dr^2} = \frac{\varkappa_0}{r} \qquad \forall r \tag{A.3b}$$

where $\varkappa_0$ is the constant of proportionality that can be set to any arbitrary constant without loss of generality. Since the ultimate goal is to derive a measure that will be optimized (maximized or minimized), a scaling constant will make no difference to the final solution of this optimization problem.

Given these assumptions, and setting the constant of proportionality to 1, we can start by integrating (A.3b) to get

$$\frac{df}{dr} = \int_{\mathscr{R}} \frac{1}{r}\, dr = \log(r) + \varkappa_1$$

where the constant of integration, $\varkappa_1$, can be solved using the initial condition (A.2c) to get $\varkappa_1 = -\log(\bar{r})$. This yields the result

$$\frac{df}{dr} = \log\frac{r}{\bar{r}}$$

which, it can be verified, satisfies each of the conditions (A.2a)–(A.2c). This solution can be further integrated to obtain

$$f = \int_{\mathscr{R}} \log\frac{r}{\bar{r}}\, dr = r\log\frac{r}{\bar{r}} - r + \varkappa_2$$

where the constant of this integration, $\varkappa_2$, can be solved using the initial condition (A.1b) to get $\varkappa_2 = \bar{r}$.

This procedure yields the final functional form for f, and recognizing the conditional (on t) aspect of this measure, we can compute the net information acquired over the entire domain $\mathscr{T}$ as

$$I = \int_{\mathscr{T}} I(t)\, dt = \int_{\mathscr{T}} \left[r(t)\log\frac{r(t)}{\bar{r}(t)} - r(t) + \bar{r}(t) \right] dt \tag{A.4}$$

Since the analyst modeling criminal recidivism has information only on a limited support of the domain $\mathscr{T}$ (e.g., the follow-up period) the measure in (3.17) appropriately restricts the computation in (A.4) to a limited support.

Note that (A.4) is a more general measure of information than the Kullback-Leibler directed divergence measure commonly used in Information Theory

(Kullback 1959). To see this, note that if the prior and posteriors were in fact proper probabilities (integrating to 1) then the measure in (A.4) could be simplified to

$$I=\int_{\mathcal{T}} r(t)\log\frac{r(t)}{\bar{r}(t)}dt-\int_{\mathcal{T}} r(t)dt+\int_{\mathcal{T}}\bar{r}(t)dt=\int_{\mathcal{T}} r(t)\log\frac{r(t)}{\bar{r}(t)}dt$$

which is the Kullback-Leibler directed divergence measure between two proper densities. Moreover, with an uninformative or constant (over the domain) prior, the minimization of information amounts to the maximization of Entropy—precisely the procedure Edwin Jaynes initially proposed (Jaynes 1957a,b).

A.2. NSDE AND NPRE ASYMPTOTIC STANDARD ERRORS

The NSDE and NPRE as derived in (3.23) and (3.24) can each be written as functions of the parameter vector β generically as:

$$\text{NSDE} = \Psi_1(\beta) \qquad \text{(A.5)}$$

$$\text{NPRE} = \Psi_2(\beta) \qquad \text{(A.6)}$$

With Σ_β denoting the asymptotic covariance matrix of the parameters β, one can use the δ-method (Greene 2000:357) to approximate the asymptotic variance of the NSDE and the NPRE as:

$$\sigma^2_{\text{NSDE}} = \left(\frac{\partial\Psi_1(\beta)}{\partial\beta}\right)'\Sigma_\beta\left(\frac{\partial\Psi_1(\beta)}{\partial\beta}\right) \qquad \text{(A.7)}$$

$$\sigma^2_{\text{NPRE}} = \left(\frac{\partial\Psi_2(\beta)}{\partial\beta}\right)'\Sigma_\beta\left(\frac{\partial\Psi_2(\beta)}{\partial\beta}\right) \qquad \text{(A.8)}$$

and the asymptotic standard errors are the square-roots of these estimates.

Note that the δ-method provides a first order approximation for the estimate *if* the function Ψ_1 or Ψ_2 are non-linear. In our case, they are linear and therefore the transformations are exact.

The asymptotic covariance matrix for the underlying parameters (Σ_β) is computed as the negative inverted Hessian of the dual objective function (evaluated at the optimal parameter values).

$$\Sigma_\beta = -\left(\frac{\partial^2 \mathscr{F}}{\partial \beta \partial \beta'}\right)^{-1} \tag{A.9}$$

where $\mathscr{F}$ is defined in (3.20).

Appendix B

Tables

This appendix provide detailed parameter estimates from models designed to estimate the IPT weights as well as the multiple-clock models summarized in the findings chapter.

Table B.1: Logistic regression results of using available attributes to predict $\tau = 1$, current offense: Violent.

Attribute	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
INTERCEPT	-1.25	0.2002	38.85	0.00
TIMESERVED	0.17	0.0065	679.78	0.00
AGEREL	0.02	0.0017	90.11	0.00
CHIST	-0.03	0.0043	36.38	0.00
SUPERVISION	-0.34	0.0316	119.05	0.00
MALE	0.44	0.0558	60.83	0.00
RACE_WHITE	-0.10	0.1252	0.65	0.42
RACE_BLACK	0.06	0.1551	0.14	0.70
ETH_HISP	0.30	0.1567	3.67	0.06
ETH_EURO	0.10	0.1462	0.51	0.48
ETH_AFRI	0.03	0.1627	0.04	0.84
ED_SCH	0.07	0.0378	3.46	0.06
ED_COL	-0.03	0.0703	0.17	0.68
MAR_SINGLE	0.04	0.0386	0.91	0.34
MAR_MARRIED	0.11	0.0522	4.08	0.04
MAR_SEPDIVW	0.01	0.0498	0.06	0.81
EMP_UNEMP	-0.02	0.0625	0.06	0.80
EMP_FULL	0.01	0.0594	0.05	0.83
EMP_PART	-0.03	0.0753	0.14	0.71

Table B.2: Logistic regression results of using available attributes to predict $\tau = 1$, current offense: Robbery.

Attribute	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
INTERCEPT	-0.34	0.2852	1.38	0.24
TIMESERVED	0.05	0.0057	91.18	0.00
AGEREL	0.01	0.0030	19.86	0.00
CHIST	0.02	0.0055	14.11	0.00
SUPERVISION	-0.04	0.0406	1.14	0.29
MALE	0.01	0.0857	0.01	0.93
RACE_WHITE	-0.11	0.1604	0.47	0.49
RACE_BLACK	-0.48	0.1868	6.57	0.01
ETH_HISP	-0.10	0.2342	0.17	0.68
ETH_EURO	-0.23	0.2232	1.02	0.31
ETH_AFRI	-0.02	0.2287	0.01	0.93
ED_SCH	0.13	0.0480	6.89	0.01
ED_COL	0.09	0.1025	0.79	0.38
MAR_SINGLE	-0.26	0.0467	29.98	0.00
MAR_MARRIED	-0.42	0.0742	31.64	0.00
MAR_SEPDIVW	-0.59	0.0785	55.88	0.00
EMP_UNEMP	0.24	0.0794	9.42	0.00
EMP_FULL	0.10	0.0773	1.66	0.20
EMP_PART	0.29	0.0917	10.34	0.00

Table B.3: Logistic regression results of using available attributes to predict $\tau = 1$, current offense: Burglary.

Attribute	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
INTERCEPT	0.14	0.1987	0.49	0.48
TIMESERVED	0.04	0.0058	47.27	0.00
AGEREL	0.02	0.0019	105.93	0.00
CHIST	0.00	0.0034	0.24	0.63
SUPERVISION	-0.20	0.0308	41.37	0.00
MALE	-0.21	0.0743	8.19	0.00
RACE_WHITE	0.01	0.1066	0.02	0.89
RACE_BLACK	-0.30	0.1415	4.45	0.03
ETH_HISP	0.09	0.1579	0.32	0.57
ETH_EURO	-0.17	0.1514	1.20	0.27
ETH_AFRI	-0.01	0.1686	0.01	0.94
ED_SCH	0.29	0.0353	66.29	0.00
ED_COL	0.09	0.0766	1.34	0.25
MAR_SINGLE	-0.55	0.0348	252.59	0.00
MAR_MARRIED	-0.58	0.0549	112.06	0.00
MAR_SEPDIVW	-0.77	0.0514	222.09	0.00
EMP_UNEMP	0.11	0.0608	3.27	0.07
EMP_FULL	0.12	0.0591	4.21	0.04
EMP_PART	0.10	0.0706	1.91	0.17

Table B.4: Logistic regression results of using available attributes to predict $\tau = 1$, current offense: Other Property.

Attribute	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
INTERCEPT	-1.53	0.1786	72.95	0.00
TIMESERVED	0.05	0.0057	86.45	0.00
AGEREL	0.00	0.0016	2.03	0.15
CHIST	0.05	0.0030	294.21	0.00
SUPERVISION	-0.26	0.0288	79.72	0.00
MALE	0.89	0.0440	411.38	0.00
RACE_WHITE	-0.03	0.1056	0.07	0.79
RACE_BLACK	-0.31	0.1354	5.17	0.02
ETH_HISP	0.17	0.1465	1.35	0.24
ETH_EURO	-0.01	0.1384	0.01	0.93
ETH_AFRI	0.15	0.1563	0.90	0.34
ED_SCH	0.13	0.0339	14.24	0.00
ED_COL	-0.31	0.0618	24.66	0.00
MAR_SINGLE	-0.26	0.0324	63.97	0.00
MAR_MARRIED	-0.41	0.0460	77.46	0.00
MAR_SEPDIVW	-0.51	0.0437	138.32	0.00
EMP_UNEMP	0.32	0.0555	33.20	0.00
EMP_FULL	0.26	0.0534	22.88	0.00
EMP_PART	0.34	0.0670	25.82	0.00

Table B.5: Logistic regression results of using available attributes to predict $\tau = 1$, current offense: Drug.

Attribute	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
INTERCEPT	-2.41	0.1887	162.50	0.00
TIMESERVED	0.07	0.0054	151.19	0.00
AGEREL	0.01	0.0014	20.02	0.00
CHIST	0.09	0.0027	979.36	0.00
SUPERVISION	-0.14	0.0288	22.99	0.00
MALE	0.79	0.0428	344.43	0.00
RACE_WHITE	-0.10	0.1170	0.76	0.38
RACE_BLACK	-0.59	0.1313	19.94	0.00
ETH_HISP	-0.07	0.1526	0.21	0.65
ETH_EURO	0.12	0.1440	0.68	0.41
ETH_AFRI	0.29	0.1481	3.80	0.05
ED_SCH	0.10	0.0310	9.57	0.00
ED_COL	-0.13	0.0632	4.52	0.03
MAR_SINGLE	0.11	0.0289	14.51	0.00
MAR_MARRIED	-0.08	0.0434	3.43	0.06
MAR_SEPDIVW	-0.12	0.0426	8.58	0.00
EMP_UNEMP	0.17	0.0519	10.86	0.00
EMP_FULL	0.19	0.0514	13.92	0.00
EMP_PART	0.07	0.0599	1.30	0.25

Table B.6: Logistic regression results of using available attributes to predict $\tau = 1$, current offense: Other.

Attribute	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
INTERCEPT	-2.14	0.2561	69.58	0.00
TIMESERVED	0.12	0.0074	249.25	0.00
AGEREL	0.00	0.0020	3.56	0.06
CHIST	0.08	0.0044	351.55	0.00
SUPERVISION	-0.09	0.0398	4.95	0.03
MALE	0.81	0.0825	96.39	0.00
RACE_WHITE	0.03	0.1588	0.04	0.85
RACE_BLACK	-0.16	0.1912	0.73	0.39
ETH_HISP	0.40	0.1955	4.13	0.04
ETH_EURO	0.10	0.1816	0.28	0.60
ETH_AFRI	0.13	0.1984	0.46	0.50
ED_SCH	-0.06	0.0447	1.69	0.19
ED_COL	-0.29	0.0914	9.73	0.00
MAR_SINGLE	0.07	0.0441	2.48	0.12
MAR_MARRIED	-0.03	0.0602	0.19	0.67
MAR_SEPDIVW	-0.11	0.0588	3.71	0.05
EMP_UNEMP	0.21	0.0747	7.76	0.01
EMP_FULL	0.25	0.0709	12.11	0.00
EMP_PART	0.22	0.0900	6.20	0.01

Table B.7: Multiple-clock models predicting rearrest, current offense: Violent.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-5.575	0.324	295.21	0.00
τ	β_0^*	1.039	0.473	4.83	0.03
a	β_1	0.103	0.043	5.86	0.02
$a \times \tau$	β_1^*	-0.158	0.062	6.47	0.01
$a \log a$	β_2	-0.031	0.009	11.36	0.00
$a \log a \times \tau$	β_2^*	0.035	0.014	6.80	0.01
t	β_3	-0.074	0.059	1.56	0.21
$t \times \tau$	β_3^*	-0.179	0.086	4.31	0.04
$t \log t$	β_4	-0.209	0.050	17.35	0.00
$t \log t \times \tau$	β_4^*	0.247	0.072	11.67	0.00

Table B.8: Multiple-clock models predicting rearrest, current offense: Robbery.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-5.824	0.440	175.07	0.00
τ	β_0^*	1.226	0.621	3.89	0.05
a	β_1	0.112	0.062	3.25	0.07
$a \times \tau$	β_1^*	-0.173	0.088	3.92	0.05
$a \log a$	β_2	-0.029	0.014	4.32	0.04
$a \log a \times \tau$	β_2^*	0.037	0.020	3.55	0.06
t	β_3	-0.188	0.067	7.79	0.01
$t \times \tau$	β_3^*	0.115	0.097	1.39	0.24
$t \log t$	β_4	-0.177	0.059	9.12	0.00
$t \log t \times \tau$	β_4^*	-0.011	0.084	0.02	0.90

Table B.9: Multiple-clock models predicting rearrest, current offense: Burglary.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-6.108	0.316	374.23	0.00
τ	β_0^*	0.869	0.450	3.73	0.05
a	β_1	0.146	0.043	11.27	0.00
$a \times \tau$	β_1^*	-0.133	0.062	4.57	0.03
$a \log a$	β_2	-0.032	0.010	11.21	0.00
$a \log a \times \tau$	β_2^*	0.028	0.014	4.06	0.04
t	β_3	-0.507	0.046	122.81	0.00
$t \times \tau$	β_3^*	0.218	0.066	10.81	0.00
$t \log t$	β_4	0.006	0.041	0.02	0.89
$t \log t \times \tau$	β_4^*	-0.082	0.059	1.94	0.16

Table B.10: Multiple-clock models predicting rearrest, current offense: Other Property.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-6.180	0.279	491.16	0.00
τ	β_0^*	1.563	0.386	16.43	0.00
a	β_1	0.198	0.037	28.33	0.00
$a \times \tau$	β_1^*	-0.251	0.051	23.95	0.00
$a \log a$	β_2	-0.047	0.008	33.45	0.00
$a \log a \times \tau$	β_2^*	0.057	0.011	25.40	0.00
t	β_3	-0.445	0.042	113.45	0.00
$t \times \tau$	β_3^*	0.114	0.059	3.66	0.06
$t \log t$	β_4	-0.014	0.037	0.15	0.70
$t \log t \times \tau$	β_4^*	-0.001	0.052	0.00	0.98

Table B.11: Multiple-clock models predicting rearrest, current offense: Drug.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-4.194	0.235	318.15	0.00
τ	β_0^*	0.201	0.330	0.37	0.54
a	β_1	-0.066	0.031	4.61	0.03
$a \times \tau$	β_1^*	-0.040	0.043	0.84	0.36
$a \log a$	β_2	0.009	0.007	1.86	0.17
$a \log a \times \tau$	β_2^*	0.008	0.009	0.79	0.37
t	β_3	-0.244	0.036	46.80	0.00
$t \times \tau$	β_3^*	0.214	0.051	17.84	0.00
$t \log t$	β_4	-0.121	0.031	15.02	0.00
$t \log t \times \tau$	β_4^*	-0.073	0.044	2.74	0.10

Table B.12: Multiple-clock models predicting rearrest, current offense: Other.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-4.394	0.369	141.71	0.00
τ	β_0^*	-0.214	0.515	0.17	0.68
a	β_1	-0.010	0.049	0.04	0.84
$a \times \tau$	β_1^*	-0.007	0.068	0.01	0.91
$a \log a$	β_2	-0.006	0.011	0.31	0.57
$a \log a \times \tau$	β_2^*	0.003	0.015	0.04	0.85
t	β_3	-0.260	0.060	18.93	0.00
$t \times \tau$	β_3^*	0.166	0.086	3.78	0.05
$t \log t$	β_4	-0.040	0.051	0.60	0.44
$t \log t \times \tau$	β_4^*	-0.114	0.073	2.40	0.12

Table B.13: Multiple-clock models predicting reconviction, current offense: Violent.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-6.137	0.402	233.54	0.00
τ	β_0^*	0.680	0.606	1.26	0.26
a	β_1	0.129	0.053	5.85	0.02
$a \times \tau$	β_1^*	-0.118	0.081	2.13	0.14
$a \log a$	β_2	-0.038	0.012	10.48	0.00
$a \log a \times \tau$	β_2^*	0.026	0.018	2.12	0.15
t	β_3	-0.117	0.072	2.63	0.10
$t \times \tau$	β_3^*	-0.032	0.107	0.09	0.76
$t \log t$	β_4	-0.137	0.060	5.31	0.02
$t \log t \times \tau$	β_4^*	0.085	0.088	0.92	0.34

Table B.14: Multiple-clock models predicting reconviction, current offense: Robbery.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-7.246	0.534	184.37	0.00
τ	β_0^*	1.533	0.774	3.92	0.05
a	β_1	0.243	0.075	10.41	0.00
$a \times \tau$	β_1^*	-0.223	0.109	4.18	0.04
$a \log a$	β_2	-0.058	0.017	11.71	0.00
$a \log a \times \tau$	β_2^*	0.048	0.024	3.85	0.05
t	β_3	-0.254	0.081	9.87	0.00
$t \times \tau$	β_3^*	0.049	0.120	0.17	0.68
$t \log t$	β_4	-0.041	0.067	0.37	0.54
$t \log t \times \tau$	β_4^*	-0.024	0.099	0.06	0.81

Table B.15: Multiple-clock models predicting reconviction, current offense: Burglary.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-7.357	0.369	397.61	0.00
τ	β_0^*	1.862	0.530	12.36	0.00
a	β_1	0.277	0.051	29.52	0.00
$a \times \tau$	β_1^*	-0.276	0.073	14.17	0.00
$a \log a$	β_2	-0.062	0.011	30.41	0.00
$a \log a \times \tau$	β_2^*	0.059	0.016	13.32	0.00
t	β_3	-0.465	0.053	77.63	0.00
$t \times \tau$	β_3^*	0.196	0.078	6.31	0.01
$t \log t$	β_4	0.071	0.045	2.44	0.12
$t \log t \times \tau$	β_4^*	-0.155	0.067	5.43	0.02

Table B.16: Multiple-clock models predicting reconviction, current offense: Other Property.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-6.790	0.324	439.76	0.00
τ	β_0^*	1.284	0.452	8.07	0.00
a	β_1	0.238	0.043	30.09	0.00
$a \times \tau$	β_1^*	-0.211	0.060	12.21	0.00
$a \log a$	β_2	-0.056	0.010	35.03	0.00
$a \log a \times \tau$	β_2^*	0.048	0.013	13.00	0.00
t	β_3	-0.440	0.048	84.72	0.00
$t \times \tau$	β_3^*	0.046	0.069	0.45	0.50
$t \log t$	β_4	-0.010	0.042	0.05	0.82
$t \log t \times \tau$	β_4^*	0.032	0.059	0.29	0.59

Table B.17: Multiple-clock models predicting reconviction, current offense: Drug.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-5.155	0.285	326.08	0.00
τ	β_0^*	0.426	0.400	1.13	0.29
a	β_1	0.005	0.038	0.02	0.89
$a \times \tau$	β_1^*	-0.080	0.053	2.30	0.13
$a \log a$	β_2	-0.007	0.008	0.69	0.41
$a \log a \times \tau$	β_2^*	0.017	0.012	2.20	0.14
t	β_3	-0.277	0.043	41.59	0.00
$t \times \tau$	β_3^*	0.311	0.062	25.55	0.00
$t \log t$	β_4	-0.042	0.036	1.31	0.25
$t \log t \times \tau$	β_4^*	-0.201	0.052	15.18	0.00

Table B.18: Multiple-clock models predicting reconviction, current offense: Other.

Component	β	$\hat{\beta}$	a.s.e	Wald χ^2	p-value
1	β_0	-5.288	0.426	154.08	0.00
τ	β_0^*	-0.526	0.610	0.74	0.39
a	β_1	0.031	0.056	0.31	0.58
$a \times \tau$	β_1^*	0.041	0.080	0.27	0.61
$a \log a$	β_2	-0.013	0.012	1.19	0.28
$a \log a \times \tau$	β_2^*	-0.009	0.018	0.26	0.61
t	β_3	-0.263	0.070	14.05	0.00
$t \times \tau$	β_3^*	0.229	0.102	5.07	0.02
$t \log t$	β_4	-0.034	0.059	0.34	0.56
$t \log t \times \tau$	β_4^*	-0.200	0.085	5.48	0.02