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An economic analysis of post- release behavior among Texas felons

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AN ECONOMIC ANALYSIS OF POST-RELEASE BEHAVIOR AMONG TEXAS FELONS

by

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ABSTRACT

During the 1980's the majority of states were mandated by court order to reduce the overcrowded conditions of their prisons. The response of some was to release prisoners in an ad hoc fashion and to use probation as an alternative to prison.

The central issue of this dissertation was the efficient allocation of resources within the criminal justice system. Specifically, four questions were addressed. What factors determined the sanction? What criminal and socio-economic characteristics distinguished successful ex-inmates? What criminal and socio-economic characteristics distinguished successful probationers. Were criminal types that were more successful under one sanction being punished via the other sanction?

A sample of 740 convicted felons from Harris County (Houston), Texas were tracked from January and February, 1980 through June 1986. Some were placed on probation while the others were sent to prison and later released.

Logit analysis was used to estimate the effect of criminal and socio-economic covariates on the probability of prison relative to the probability of probation. Empirical results suggested that black offenders who were convicted of personal injury crimes or theft offenses were more likely to be sent to prison than placed on probation. Offenders were more likely to be placed on probation if they had a job and had been released on bond.

Duration analysis was used to estimate hazard rates. These were used to link criminal justice and socio-economic factors to the timing and probability of recidivating. The relative chance of failure decreased for ex-inmates who had been incarcerated less than the average prison term and then were released to a halfway house or to family members. Black first time offenders who sought counseling for substance abuse problems were the most likely successful probationers. Police presence was a deterrent and increased police productivity improved the chances of detection. The relative deprivation hypothesis was supported.

Policy recommendations included extending the length of probation, reducing the length of prison terms, and requiring closer supervision for all upon re-entry into society.

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CHAPTER 1: INTRODUCTION

The major focus of this dissertation was an analysis of criminal recidivism, the factors which alter the timing of recidivism and how to use that information to reduce the cost of crime. What made this project unique was the opportunity to compare probationers and ex-inmates. Of primary interest was the effect of economic variables and other personal characteristics on the distribution of failure times for these two groups.

The timing of recidivism was part of the larger problem of state provided criminal correctional services. A March 1986 poll conducted by the National Institute of Justice revealed that among criminal justice officials the number one problem was prison and jail crowding. The problem was partially attributed to the lack of funds for additional jail space. Most states postponed new construction or any other action until faced with a court order which mandated a remedy to the situation. As recently as 1984, all but 8 states were under court order to reduce prison populations. The response of some states was to release inmates in an ad hoc fashion and to use probation as an alternative to prison. Many ex-offenders subsequently returned to criminal activities. Petersilia et. al.. (1985) found, in a study which followed felony probationers for 40 months, 51 percent were charged and convicted of new crimes.

Four questions have been addressed. What factors determined the sanction imposed on a convicted felon? What criminal and socio-economic characteristics distinguished successful ex-inmates? What criminal and socio-economic characteristics distinguished successful probationers? Were there criminal types that were given one sanction but performed better under the other sanction? The first question addressed the issue of placing on probation offenders who should have been incarcerated. The second and third questions addressed the issues of what factors lead to the greatest chance of success after release. The fourth question addressed the possible need for changes in sentencing policies. Success was translated into lower future costs of crime.

The work has been organized in the following fashion. Chapter II contains the literature review of work done on the economic model of crime. Chapter III presents the theoretical economic model of crime. Chapter IV describes the data and Chapter V explains the statistical methods used in the analysis. The final chapter contains the empirical results and policy recommendations.

CHAPTER 2: Literature Review

Economists have long viewed the criminal as a rational individual who allocated time between legal and illegal activities based on the relative expected returns. Becker (1968) was the first to argue that criminals maximized utility given opportunity costs and changes in opportunity costs changed behavior. The expected return to illegal activities was partially determined by the probability of apprehension and the severity of the punishment once captured. Therefore, if society desired to deter criminals, it needed to increase the probability of detection and arrest and increase the severity of punishment. The overriding issue of early research (Becker 1968, Ehrlich 1973, Sjoquist 1973, Block and Heineke 1975, and Heineke 1978) was the absolute and relative effectiveness of deterrent policies.

Most authors used the von Neumann Morgenstern utility maximization framework to incorporate the uncertainty of income from criminal activities. Income was uncertain because the outcome of crime was uncertain. The income from legal activities was usually considered to be certain although Schmidt and Witte (1984) recently developed a model which included the possibility of unemployment and hence uncertain legal income. The individual maximized expected utility which was a function of income generated from both legal and illegal activities. The individual allocated time among legal and illegal endeavors and leisure with the possibility of corner solutions.

The models predicted that the increase in the probability of apprehension or the severity of punishment were deterrents and that the elasticity of time in illegal activities with respect to the probability of apprehension was greater than the elasticity of time in illegal activities with respect to the severity of punishment. Increasing the probability of being caught was a greater deterrent than increasing the severity of the punishment.

The models had problems and were subject to criticism. Most assumed monetary equivalents of non-monetary costs involved in both legal and illegal endeavors. These included the psychic cost of legitimate work, the loss of reputation if detected committing a crime, and the psychic cost of spending time in jail. A monetary equivalent existed if, given a particular allocation of time and income, there was some income level with no penalty and no legitimate work that was low enough such that the person was indifferent between the income levels. Heineke (1978) and Block and Heineke (1975) cast doubt upon the existence of such monetary equivalents, "...it is not generally true that monetary equivalents exist to labor and penalty attributes of an offense." If for example, at the optimal allocation of time between activity types, the marginal rate of substitution between wealth and the penalty was infinite then no monetary equivalent for the penalty existed.

Heineke (1978) also showed that the specification of the monetary equivalent function determined the outcome of comparative statics. A recursive model resulted when the cost of crime was not included in the supply function for legitimate work and the psychic cost of work was not included in the supply function for criminal activities. Legal and illegal markets were independent of each other. The person first determined the amount of legitimate labor time and then the amount of criminal time. Consequently, legitimate activities were independent of initial wealth levels, the probability of apprehension, mean preserving changes in the dispersion of the return to illegal activities, changes in the returns to illegal activities, and the severity of punishment. This model also produced the perverse result that, with respect to the returns on legitimate activities, legal and illegal time were gross complements.

The preceding assumed independence of legal and illegal markets and implicitly assumed leisure time was variable. If leisure time was fixed the comparative static results changed. Legal time allocation became a function of all of the same parameters as illegal time allocation and any parametric change on criminal time allotment had a direct and reverse effect upon the legitimate time allocation. Heineke (1978) questioned whether either type of model, fixed or variable leisure time, described the criminal choice problem.

More realistic models entered the amount of time devoted to legal and illegal activities directly into the utility function. The less restrictive model was not recursive and did not require a specific monetary equivalent. The interpretation was that psychic costs and benefits of either activity entered directly into the utility function and the costs represented in the income equation were purely monetary. Heineke (1978) and Schmidt and Witte (1983) presented this specification and both had similar results. Non-ambiguous comparative static results were only possible under strict assumptions regarding risk preferences and cross second partial derivatives of the utility function. Schmidt and Witte found increasing the probability of arrest was a deterrent only when an individual was assumed to be no more than risk neutral with constant or <u>increasing</u> absolute risk aversion. The normal assumption was decreasing absolute risk aversion. It was also necessary to assume income and leisure to be separable in the utility function.

Although the more realistic models provided ambiguous theoretical results, they contributed significantly toward indicating which variables to enter into equations for legal and illegal time in empirical research. This proved to be especially valuable in light of the comparative static results. As Heineke and Block (1975, p. 323) noted, "In the area of law enforcement as in taxation, policy recommendations do not follow from theory but rather require empirical determination of relative magnitudes."

<u>Empirical Models: Macro Data</u>

The deterrent hypothesis has been tested using data from a myriad of sources - U.S. governmental agencies, state and local agencies, English police districts, Canadian Provinces, Australian

Territories, and Japanese jurisdictions. The efforts have ranged from single equation models using cross-sectional data to simultaneous equation systems models using pooled time-series cross-section data sets. The vast majority of the work supported the deterrent hypothesis. The effects of the costs and benefits of illegal activity and various socio-economic factors were also tested. These factors were measured in terms of income variables, value of property transferred, sex, race, and population density, among others. Invariably all the studies had some measure of the certainty and severity of punishment since the primary purpose was to test the deterrent hypothesis.

Isaac Ehrlich (1973) presented empirical results with his theoretical exposition. He used state level data from the years of 1960, 1950, and 1940. Data limitations restricted him to Ordinary Least Squares (OLS) for various crime types with the 1950 and 1940 data. The results of this specification supported the deterrent hypothesis. He recognized the simultaneity of the offense supply function and the law enforcement production function and acknowledged the possibility of biased estimates. The simultaneity problem existed because, in the aggregate, the amount of time allocated to criminal activity contributed to the amount of law enforcement and vice versa. To correct for the bias, Two-Stage Least Squares was used. Ehrlich's results generally supported the hypothesis that probability of apprehension and the severity of punishment both had a deterrent effect. Ehrlich also found that the elasticity of the crime rate with respect to probability of arrest was greater than the elasticity with respect to the severity of punishment. Increasing the probability of arrest was a more effective deterrent policy than was the lengthening of the average prison sentence.

Other researchers used state level or comparable data. Lin and Loeb (1980) used data from 32 Mexican states to determine tourism's effect upon aggregate crime rates. Tourism directly affected property crimes, e.g. larceny and burglary, but did not affect personal injury crimes, e.g. murder and rape. Their results also supported the deterrence hypothesis. Sommers (1980) used state level data to test whether gun control was a deterrent to crime. Her model contained only one equation but she concluded the deterrent hypothesis could not be rejected and states with gun control laws had lower crime rates than those without such laws. Avio and Clark (1976) analyzed the deterrent hypothesis with Canadian provincial data. The data had limited socio-economic information and some provinces had to be eliminated. This precluded correcting for serial correlation produced by pooling cross-section data. They determined the probability of apprehension was a deterrent but the length of sentence was insignificant in discouraging crime. The data problems made their conclusions tenative at best. Finally, Withers (1984), using Australian Territorial data, found support for the deterrent hypothesis and did not find income to be significant in the choice decision. He used only one equation and ignored the simultaneity problem.

Numerous researchers argued that since the policy decisions were made predominantly at the local level data should reflect local crime rates, average city income levels, and local expenditures. Certainly, the length of sentence imposed was not determined by local authorities but the attitude toward crime within the local area indirectly affected the severity of some sentences. These authors used cross-sectional data reflecting city specific averages. Sjoquist (1973) used a cross-sectional sample of approximately 50 communities with populations ranging from 25,000 to 200,000 that were relatively far from other major urban areas. He argued this reduced the possibility of criminals migrating among cities in response to differential law enforcement campaigns. Measures of some variables continued to be at the state or county level. Sjoquist's model consisted of only one equation which he tested with various proxies for the risk of capture and punishment. His log-log specification strongly supported deterrence and the premise that certainty of punishment was a greater deterrent than the severity of punishment. Income, measured by the annual manufacturers' income of a respective county, was significant but had a positive sign. The percent of non-white population and the unemployment rate had the expected positive sign.

Swimmer (1973) developed a two equation simultaneous-equation model using city-wide data from cities with at least 100,000 residents. Again, certainty and severity of punishment were found to be significant deterrents. As with Sjoquist, the income variable was not significant. Unlike Sjoquist, the unemployment rate was also not significant. Mathur (1978) criticized Swimmer's measurement of police expenditures. Swimmer used the per capita property tax as a proxy. Mathur argued general revenues provided a better proxy and substituted it into his three equation model. In addition to supporting the deterrence hypothesis, he found evidence of an inverse relationship between the severity of punishment and the probability of being punished. He contended this helped explain why juries had been willing to find a defendant guilty of a lesser offense and why some judges had been willing to allow plea bargaining to lesser offenses.

Variants of models previously discussed were estimated with city-wide data. Each introduced a new variable or made some adjustment for measurement error, see Myers (1982). In general, the deterrent hypothesis was not rejected and the certainty of punishment was a stronger deterrent than severity of punishment. See for example Phillips and Votey (1975), Corman (1981), Sesnowitz and Hexter (1982), Buck et. al. (1983), Moheb et. al. (1983) and Vanagunas (1984).

The wide variety of models with different specifications, functional forms, and assumptions had common problems. The primary problem was the measurement error in aggregate data. The dependent variable in the supply of crime equation was usually some measure of a crime rate which ranged from an overall crime rate to the crime rate for a specific crime type.

The inherent problem with this variable was in the reporting of crime by the public, and in some instances, the reporting by the police. If there was general dissatisfaction with law enforcement agencies and a perception that little could be done toward crime control, the public may not have reported the true number of crimes committed. Conversely, announced changes in policies or expenditures on crime control may have resulted in an apparent increase in crime. An increase of the police force and the visibility of officers may have lead some citizens to report crimes which had previously gone unreported. The implementation of the "911" emergency phone number reduced the cost of reporting crime and possibly produced an increase in the crime rate.

The efficiency of police departments was measured by the ratio of solved crimes to reported crimes. One way of increasing the ratio was to underreport the number of crimes.. For example, they may have classified a reported burglary as missplaced property by the owner and hence reduced the number of reported crimes. Conversely, if a department was seeking funds it had the incentive to overreport in relevant categories to present a picture of need. Also, by classifying crime in less serious categories it was possible to report declines in serious crimes overall.

The impact of manipulating reported crimes carried over into crime clearance rates. If the number of crimes declined and the number solved increased the department appeared to be more efficient. Similar problems existed for other ratios involving conviction rates or imprisonment rates.

Many studies used the state average of prison entries as a measure for certainty of punishment given conviction which ignored other non-monetary forms of punishment. Many offenders were placed on probation and not sent to prison. These offenders did not appear in the prison enrollment figures and caused an underreporting of offenders punished. The use of time sentenced as a measure of severity of punishment was inaccurate whenever it diverged from the actual time served. State averages of imposed sentences generally overestimated the actual time served by offenders.

The modeling procedures were also criticized. The problem of simultaneity was mentioned previously. Taylor (1978) pointed out some problems in identifying the structural equations of the empirical crime model. Researchers did not concur on what to include in the offender supply function. Variables such as age, appeared in some models and not in others. No well-developed theory suggested what variables should be included. This produced a variety of combinations of restrictions for the structural equations of the models. "Since the proper exclusion of predetermined variables is crucial for identifying structural equations, the lack of formal theory has led some critics to the conclusion that the models of crime are not adequately identified and consequently that the statistical results are unreliable..." (Taylor 1978, p. 59). Fisher and Nagin (1978) warned, in terms of interpreting results, the dangers of mis-identification may be greater than those of non-identification.

Empirical Models: Micro Data

The identification problem and other problems associated with aggregate data induced many researchers to utilize individual-level, or micro, data. Manski (1978) pointed out micro data provided the opportunity to incorporate a well developed body of knowledge regarding individual behavior and choice. Micro data was superior for a myriad of reasons. It retained information lost in aggregation. Individual offender characteristics were available and the measure of criminal activity came directly from a person's criminal record or personal interviews. The personal number of arrests, convictions, or incarcerations during a particular time period were often used.

Micro data permitted analysis at the level where decisions were made. The effect of deterrent policies or specific rehabilitation programs could be tested across individuals, or groups of individuals with common characteristics.

Individual-level data posed problems absent in aggregate data. Data collection was the first major issue. Equally important issues included the definition of recidivism, the length of the follow-up period, and technical econometric problems. Reliable results required personal information on a relatively large group of individuals, some proportion of which were criminals. Attitudes toward personal privacy made reliable data on the general population difficult to obtain. The alternative was to collect data on current or past criminals. Data was available either through personal interviews or from criminal justice information systems.

Both sources were subject to criticism. Interviews were extremely costly methods of data collection and truthfulness of the responses was questioned. Data collected from criminal justice agencies only reflected the crimes detected, not unreported and unsolved crimes. Additionally, not all jurisdictions were willing to open their files for the sake of research.

These sources often precluded random assignment of participants to experimental groups. Judges, juries and society were reluctant to sentence convicted offenders via a random lottery. Laws prohibited involuntary participation in rehabilitation programs and as such participants were not always a representative sample of the criminal population. Investigators had to be content with quasi-experimental data.

The second issue centered on the definition of recidivism. Data sets containing observations on criminals changed the focus of research. Macro data studies addressed general criminal activity. Micro data studies addressed the occurrence of repeated criminal activity within a group of known criminals. Numerous definitions had been proposed by criminal justice professionals. One general definition of recidivism was, "the proneness of many criminals to continue a life of crime." Barnes and Teeters (1959). More precise definitions were used. Rearrest, reconviction, parole or probation violations, and reincarceration were the most common. Some definitions required a minimum level offense to be committed before a criminal was classified as a recidivist. An armed robber did not recidivate by being arrested for drunk driving or a relatively minor misdemeanor charge. If some minimum did exist, its establishment was usually arbitrarily determined. Some researchers imposed the extreme requirement that an offender recidivated for the same type of crime. The source of data often dictated the definition. Research using police rap sheets would use rearrest information while work done by prison officials used the reincarceration definition.

Any definition was susceptible to measurement error. Rearrest figures ignored the principle of innocent until proven guilty. A person may subsequently have been found innocent even though the rearrest definition determined recidivism. If recidivism was defined as reconviction, problems occurred with plea bargaining. The offense for which a criminal was charged may have been more severe than the actual convicted offense. This presented particular problems when an attempt was made to measure the seriousness of the recidivating offense. Reconviction also failed to capture offenses which were committed but did not result in a conviction. Recidivism measured by reincarceration had the problem of missing offenders who were convicted of crimes that did not result in a prison sentence.

Technical violations of conditions of probation or parole also presented definitional problems. These violations ranged from failing to appear for an appointment with a supervising officer to frequenting a lounge which served alcoholic beverages. A probationer or parolee could be incarcerated for violating such conditions. Complicating the issue, probation or parole could be revoked at the discretion of the supervising officer and/or judge. The violation that caused the offender to be incarcerated may have been the second or third chance given by the officer.

The length of the follow-up period was an issue. It was necessary for time to elapse but lengthy follow-up periods were costly and results for policy decisions were often needed in the short run. Waldo and Chiricos (1974) showed that a program which was relatively more effective at the six month mark could be the less effective program at the twelve and thirty-nine month mark. One of the longest follow-up intervals was 18 years by Kitchener, Schmidt and Glaser (1977). Follow-up periods were predominantly from six months to two years in length.

Researchers used various regression methods to test their models. The dependent variable was usually some measure of recidivism which was limited in its range of values. If the measure indicated only the occurrence or non-occurrence of a recidivating offense the dependent variable was restricted to values zero or one. If the number of arrests or convictions or the length of time before failure was used, the measure was truncated at zero. It was critical for any researcher to recognize the limitations of the dependent variable and use appropriate methods. Econometricians had long been providing techniques for similar type variables in other fields of economics.

Tobin (1958) was the first when he presented the tobit model in an analysis of durable goods purchases. His dependent variable was the ratio of expenditures on durable goods to income which ranged in value from zero to one. Zero indicated no purchases of durable goods during the sample period. He used maximum likelihood estimation techniques to obtain the estimates. Modifications of this approach have been used extensively in other areas of economics. In labor economics it indicated the success or failure of finding employment. In consumer economics it represented the purchase or non-purchase of a particular product. These have become known generally as tobit, or probit, models.

Numerous variations of the tobit model have been used to test economic models of crime. Witte (1980) used a tobit model and showed that deterrent elasticities were significant but varied across criminal types. She used a zero-one outcome measure and was among the first to use individual-level data. Sickles, Schmidt and Witte (1979) presented a simultaneous tobit model to test for the endogeneity of income with respect to criminal behavior and concluded that criminal behavior did not affect wages but the level of wages did affect the probability of criminal activity. Their dependent variable was the total time sentenced to prison during the follow-up period.

Different probability distribution assumptions for the occurrence of a success produced variations of the tobit model. Myers (1983), Witte and Schmidt (1979), and Witte (1980) assumed a logistic distribution and estimated a logit model.

Myers found income had a stronger effect on the probability of recidivating than either the probability of capture or the severity of the punishment. His study suffered from a relatively short follow-up period of only one year. Most work cited thus far using tobit or logit had an average follow-up period of three years.

In her 1980 paper, Witte also tested a logit model and found similar results as had been found using the tobit model.

Witte and Schmidt used a polytomous logit model and tested a model with four different outcomes. The parameters measured the change in the probability of being convicted of an offense, e.g. a property offense, relative to the probability of a different outcome, e.g. no conviction or conviction of a different crime. They found youth, many prior convictions, numerous rule violations, alcoholism, and drug addiction all increased the probability of being convicted of a crime relative to being convicted of no crime. They also found a person supervised upon release was more likely to be convicted of "other" crimes than of personal or property crimes. This may have been a function of violating parole without actually committing a more serious crime.

Good, Pirog-Good, and Sickles (1985) used a simultaneous probit model to test the relationship between employability and criminal activity of youth. Their analysis was based on youths who were enrolled in a youth crime prevention program in Philadelphia. They determined a cycle of criminal activity and employability. The greater the criminal activity the less likely the chances for employment and the reduced opportunities for employment. The reduced opportunities for employment lead to further crimes. They also determined, however, the cycle could be broken by improving employment possibilities. An increase in employability reduced criminality by 71 percent. They also found that as more time passed since the most recent police contact the probability of committing another crime decreased. Job training and public employment programs were suggested as possible tools to be used to break the cycle.

The tobit and logit models were useful methods to use with individual-level data and for handling a limited dependent variable. However, a major weakness of the models was the inability to differentiate among recidivists with respect to the timing of failure. A dichotomous variable was time invariant at the follow-up date. All that was known was that the person did or did not recidivate before the follow-up date. A person who recidivated six weeks after release was viewed the same as someone who recidivated at the six month mark. A measure of the time to failure provided more information than a dichotomous variable. The timing of recidivating became recognized as being as important as recidivating.

Empirical Models: Duration Data

The success of an offender was more accurately measured by the amount of time he or she remained violation free than by the occurrence or non-occurrence of a recidivating offense. A person who remained criminally inactive for two years and then recidivated was considered more of a success than the person who committed a similar crime immediately upon release. Even if all subjects eventually recidivated, time to failure was of interest to supervisory officers who needed to anticipate when a person was most likely to need closer supervision. From a statistical point this information made the estimates more efficient by using all of the available information of a variable.

When assessing the length of time to failure, the data was classified as duration data. The duration measured was the time until a recidivating offense occurred. These data had particular characteristics, censoring and truncation, which were easily handled by survival analysis. Duration analysis has been used in several other areas of research. It was more commonly known as reliability research in industrial engineering. The interest there was the duration before a piece of machinery fails. Labor economist have used duration analysis to study which factors contribute the length of employment and unemployment spells as well as the length of strikes. Health economist were interested in the effect of income subsidies on the duration of someone's life. Demograghers used the methods to estimate lifetimes, marriage spells, and durations between children. Biostatasticians referred to the methods as survival analysis. Applications included testing of the effectiveness of new or experimental drugs. Only relatively recently has duration analysis been applied to criminology in general and the economics of crime in particular.

A wide variety of models have been postulated to test different distributions for the survival times. Work by Kitchener, Schmidt and Glaser (1977) and Hoffman and Stone-Meierhoeffer

(1979) and others used only the cumulative percentages to measure recidivism rates and found that rates were highest during the early periods, declining gradually in subsequent ones. This evidence and frequency distributions of times to failure lead to assuming distributions which had high probability of failure in the early time periods and relatively lower probabilities in later periods.

Stollmach and Harris (1974) applied survival analysis to compare failure rates of offenders released from half-way houses versus those released directly from prison. They assumed the dependent variable followed an exponential distribution and demonstrated that the timing and probability of recidivating for those who completed half-way house tenure was significantly better than those released directly from prison. Their data consisted of parolees released directly from institutions and parollees who were first processed through a half-way house. A major problem they acknowledged was the fact that 40% of offenders initially released to half-way houses violated parole before they were released, and hence were returned to prison. This reduced the sample in the half-way houses to include those who were most likely to succeed. Their major contribution was displaying the statistical methodology.

Maltz and McCleary (1977) pointed out that the Stollmach and Harris model implicitly assumed everyone would recidivate if given enough time. They modified the exponential which allowed a particular percentage of releasees to never recidivate. They employed both the Stollmach and Harris model and their own with

Illinois parolees and concluded their method was superior in methodology as well as fitting the data better. One weakness however was the assumption that the probability to recidivate at any given time, the hazard rate, was invariant to time. This issue was addressed by Bloom (1979) who developed a model in which the hazard rate was dependent upon time. This incorporated the idea that a releasee's probability to recidivate three months into parole or probation may differ from the probability to recidivate three years after release. For example, a drug addict was much more likely to recidivate soon after release from a rehabilitation program than one who remained drug free for several years.

Previous use of survival analysis had been confined to a simple estimate of the survival function. These were known as unconditional survival functions and were based on the survival times for the group. Few authors divided the sample on the basis of some categorical variable and compared respective survival functions. Schmidt and Witte (1977) and Witte (1980) were the first to estimate and distinguish between unconditional distribution of failure times and distribution conditional upon personal characteristics. This allowed the mean of the distribution to be dependent upon personal characteristics as well as time at risk. They used the truncated lognormal distribution for the dependent variable to evaluate the effectiveness of two pre-release juvenile correctional programs and to determine which personal traits best explained survival times. Their data consisted of 2216 persons released from prison during the first six months of 1975. They determined the type of individual likely to return the soonest was young, single, and uneducated, had many previous convictions and rule violations, and had committed a crime which was not a personal injury crime.

Distinguishing between the unconditional and conditional survival function was a critical development in the field. Hazard rates, the probability of a ex-offender recidivating in a particular period given he or she had not recidivated thus far, were derived from survival functions. The more sophisticated models allowed for varying hazard rates across time. Generally, hazard rates were expected to be greatest in early periods and to decline over time. This was analogous to the results found by Kitchener et. al. mentioned earlier. Two reasons were given for the declining hazard rates. The first was state dependence. The length of the period in a particular state, i.e. criminally inactive, determined the likelihood the person would move out of that state. The greatest probability of failure occurred in the months immediately following release. If state dependency was absent declining hazard rates were explained by heterogeneity. Heterogeneity was defined as unobserved and unmeasured personal characteristics that caused some offenders to recidivate at different times at risk than other offenders. Some offenders may have been more prone to crime than other offenders and recidivated soon after release. That left the offenders who were relatively less likely to recidivate at risk and produced a decline in the overall hazard rate. Individual hazard rates were invariant to time but because of heterogeneity the hazard rate for the group appeared to be duration dependent.

Testing for heterogeneity generally required a time series of data on personal characteristics of individuals in the study group. Data of this sort was only available by repeated interviewing of the study subjects. Heckman (1981) showed how useful this type of data was in estimating the probability of employment of women given different personal characteristics. Unfortunately, data in criminal justice research was not as detailed and complete. Usually, only one follow-up date was available. This made distinguishing between heterogeneity and state dependence more difficult but not impossible. Heckman (1982) demonstrated techniques to be used when only one follow-up interview was possible.

Additionally, many predictors of recidivism were time dependent. Employment status, income, age, marital status, and drug or alcohol dependency, all had the potential of changing over time. Heckman and Singer (1986) developed an econometric framework from which models of varying types of timing schemes were derived. They recommended a general computational algorithm which used a flexible Box-Cox hazard and allowed for scalar heterogeneity and various distributional assumptions for the error term.

Research in the field was originally restricted to aggregate data and aggregate models. The availability of individual level data facilitated the development of models designed to identify criminal types most likely to succeed. The effectiveness of criminal justice policies could also be estimated. The most recent contribution came from introduction of duration data and survival time models.

This dissertation used duration analysis to determine the criminal types most likely to be successful probationers and the criminal types most likely to be successful ex-inmates. The results assisted in sentencing criminals in an attempt to reduce the number of repeat offenders and the future cost of crime.

CHAPTER 3: A THEORETICAL ECONOMIC MODEL OF CRIME

The classical economic model of crime evolved from work by Becker (1969), Heineke (1978), and Schmidt and Witte (1984). Because the decision to commit a crime was fundamentally a time allocation problem under uncertainty, variations of the von Neuman-Morgenstern expected utility function were used. Time allocated for crime was not used for legitimate activities and any crime had an associated risk of failure which meant detection, arrest, conviction, and punishment. In some models, the risk of unemployment made legal work uncertain. Utility was a function of income and leisure or alternatively a function of income and time allocated to legal or illegal work. With either specification of the utility function the individual placed intrinsic value on time devoted to legal, illegal, and leisure activities. The general framework used to analyze the allocation of time between legal and illegal activities is discussed below.

Determinants of Utility

Utility is derived from income and leisure. The general form of the utility function is U(I,N), where I is income and N is leisure. Because of the limited number of hours in a day, leisure is a function of t_1 and t_2, the amount of time allocated to legal and illegal activities respectively. Mathematically,

$$N = 24 - t_1 - t_2. \tag{3.1}$$

Income originates from one or more of three sources - legitimate income, net income from crime, and initial wealth. The uncertainty of income from all sources except initial wealth produces 10 different states for income which appear in Column 2 of Table 3.1. The probability of unemployment is e, p_a is the probability of arrest, $p_{c|a}$ is the probability of conviction given arrest, $p_{f|c}$ is the probability of fine given conviction, and $p_{p|c}$ is the probability of prison given conviction. The probability of probation, given conviction, $p_{pr|c}$, is $1 - p_{f|c} - p_{p|c}$. The j in the penalty function F^j designates different forms of punishment which include arrest, fine, prison, and probation. The likelihood of each state of income appears in Column 3 of Table 3.1. Each p_k represents the probability of the k^{th} state.

Legal income, $L(t_1,\beta)$, is dependent upon the amount of time allocated to legal work, t_1, and the shift parameter β, the return on the work effort, i.e. the wage rate. It is assumed $\partial L/\partial t_1 > 0$ and $\partial L/\partial \beta > 0$.

Analogously, illegal income, $G(t_2,\phi)$ is dependent upon the amount of time devoted to crime, t_2, and the return on crime, ϕ. ϕ is a shift parameter. Unsuccessful criminals incur costs represented by one of four functions. $F^1(t_2,\alpha^1)$ represents the cost of a crime only if an arrest occurs. $F^2(t_2,\alpha^2)$ and $F^3(t_2,\alpha^3)$ are the costs if an individual is fined and if the individual is placed on probation respectively. $F^4(t_2,\alpha^4)$ is the cost of a prison term. It is assumed $\partial F^j/\partial t_2 > 0$ for j=1,2,3,4. The more time a person devotes to crime the greater the probability of paying for deviant behavior. Professional criminals could become adept enough to avoid capture but it is assumed this is outweighed by the resources of the local law enforcement agencies. The argument αj represents the deterrent measures taken by society - certainty and severity of the respective punishment. Therefore, $\partial Fj/\partial \alpha j > 0$. Net return on criminal activity is $G(t_2,ø) - Fj(t_2,\alpha j)$ and must to be negative if a sanction is to be an effective deterrent.

Finally, the individual has some initial wealth, W_0, which produces income and is independent of any time allocation.

First Order Conditions

Given the ten possible states of income and the associated probabilities expected utility is:

$$E(U)=p_1U(I_1,N)+ p_2U(I_2,N)+ p_3U(I_3,N)+ p_4U(I_4,N)+ p_5U(I_5,N)+$$
$$p_6U(I_6,N)+ p_7U(I_7,N)+ p_8U(I_8,N)+ p_9U(I_9,N) + p_{10}U(I_{10},N)$$
$$= \Sigma p_kU(I_k,N), \ k = 1,2, \ldots 10. \qquad 3.2$$

First Order Conditions ensure the individual allocates time such that the net expected marginal return on each respective activity equals 0.

For optimal allocation of legitimate work $\partial E(U)/\partial t_1 = H_1 = 0$.

$$H_1=p_1[\partial U/\partial I_1{}^*\partial I_1/\partial t_1+\partial U/\partial N^*\partial N/\partial t_1]+$$
$$p_2[\partial U/\partial I_2{}^*\partial I_2/\partial t_1+\partial U/\partial N^*\partial N/\partial t_1]+$$
$$p_3[\partial U/\partial I_3{}^*\partial I_3/\partial t_1+\partial U/\partial N^*\partial N/\partial t_1]+$$
$$p_4[\partial U/\partial I_4{}^*\partial I_4/\partial t_1+\partial U/\partial N^*\partial N/\partial t_1]+$$

$$p_5[\partial U/\partial I_5{*}\partial I_5/\partial t_1+\partial U/\partial N{*}\partial N/\partial t_1]+$$
$$p_6[\partial U/\partial I_6{*}\partial I_6/\partial t_1+\partial U/\partial N{*}\partial N/\partial t_1]+$$
$$p_7[\partial U/\partial I_7{*}\partial I_7/\partial t_1+\partial U/\partial N{*}\partial N/\partial t_1]+$$
$$p_8[\partial U/\partial I_8{*}\partial I_8/\partial t_1+\partial U/\partial N{*}\partial N/\partial t_1]+$$
$$p_9[\partial U/\partial I_9{*}\partial I_9/\partial t_1+\partial U/\partial N{*}\partial N/\partial t_1]$$
$$p_{10}[\partial U/\partial I_{10}{*}\partial I_{10}/\partial t_1+\partial U/\partial N{*}\partial N/\partial t_1]=0. \qquad 3.3$$

By the income equation $\partial I_1/\partial t_1 = \partial I_3/\partial t_1 = \partial I_5/\partial t_1 = \partial I_7/\partial t_1 = \partial I_9/\partial t_1 = L_t$ where $L_t = \partial L/\partial t_1$ and $\partial I_2/\partial t_1 = \partial I_4/\partial t_1 = \partial I_6/\partial t_1 = \partial I_8/\partial t = \partial I_{10}/\partial t_1 = 0$. From the leisure equation $\partial N/\partial t_1 = -1$. If $U_I = \partial U/\partial I$ and $U_N = \partial U/\partial N$ then equation 3.3 simplifies to equation 3.4.

$$H_1=p_1[U_I(I_1,N){*}L_t-U_N(I_1,N)] + p_2[-U_N(I_2,N)] +$$
$$p_3[U_I(I_3,N){*}L_t-U_N(I_3,N)] + p_4[-U_N(I_4,N)] +$$
$$p_5[U_I(I_5,N){*}L_t-U_N(I_5,N)] + p_6[-U_N(I_6,N)] +$$
$$p_7[U_I(I_7,N){*}L_t-U_N(I_7,N)] + p_8[-U_N(I_8,N)] +$$
$$p_9[U_I(I_9,N){*}L_t-U_N(I_9,N)] + p_{10}[-U_N(I_{10},N)] = 0. \qquad 3.4$$

In summation notation:

$$H_1 = \sum_{\substack{k=1,3,5,\\7,9}} p_k[U_I(I_k,N){*}L_t-U_N(I_k,N)] + \sum_{\substack{k=2,4,6,\\8,10}} p_k[-U_N(I_k,N)] = 0. \qquad 3.5$$

The optimal allocation of time toward crime is $\partial E(U)/\partial t_2 = H_2 = 0$.

$$H_2=p_1[\partial U/\partial I_1{*}\partial I_1/\partial t_2+\partial U/\partial N{*}\partial N/\partial t_2]+$$
$$p_2[\partial U/\partial I_2{*}\partial I_2/\partial t_2+\partial U/\partial N{*}\partial N/\partial t_2]+$$
$$p_3[\partial U/\partial I_3{*}\partial I_3/\partial t_2+\partial U/\partial N{*}\partial N/\partial t_2]+$$

$$p_4[\partial U/\partial I_4{}^*\partial I_4/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]+$$
$$p_5[\partial U/\partial I_5{}^*\partial I_5/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]+$$
$$p_6[\partial U/\partial I_6{}^*\partial I_6/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]+$$
$$p_7[\partial U/\partial I_7{}^*\partial I_7/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]+$$
$$p_8[\partial U/\partial I_8{}^*\partial I_8/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]+$$
$$p_9[\partial U/\partial I_9{}^*\partial I_9/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]+$$
$$p_{10}[\partial U/\partial I_{10}{}^*\partial I_{10}/\partial t_2+\partial U/\partial N^*\partial N/\partial t_2]=0. \qquad 3.6$$

By the income equation $\partial I_1/\partial t_2 = \partial I_2/\partial t_2=G_t$, $\partial I_3/\partial t_2 = \partial I_4/\partial t_2=G_t - F_t^1$, $\partial I_5/\partial t_2=\partial I_6/\partial t_2=G_t - F_t^2$, $\partial I_7/\partial t_2 = \partial I_8/\partial t_2=G_t - F_t^3$, $\partial I_9/\partial t_2 = \partial I_{10}/\partial t_2=G_t - F_t^4$, and by the leisure equation $\partial N/\partial t_2 = -1$. Again, $U_I = \partial U/\partial I$ and $U_N = \partial U/\partial N$ and Equation 3.6 simplifies to 3.7.

$$H_2 = p_1[U_I(I_1,N)^*G_t-U_N(I_1,N)] +$$
$$p_2[U_I(I_2,N)^*G_t-U_N(I_2,N)] +$$
$$p_3[U_I(I_3,N)^*(G_t-F_t^1)-U_N(I_3,N)] +$$
$$p_4[U_I(I_4,N)^*(G_t-F_t^1)-U_N(I_4,N)] +$$
$$p_5[U_I(I_5,N)^*(G_t-F_t^2)-U_N(I_5,N)] +$$
$$p_6[U_I(I_6,N)^*(G_t-F_t^2)-U_N(I_6,N)] +$$
$$p_7[U_I(I_7,N)^*(G_t-F_t^3)-U_N(I_7,N)] +$$
$$p_8[U_I(I_8,N)^*(G_t-F_t^3)-U_N(I_8,N)] +$$
$$p_9[U_I(I_9,N)^*(G_t-F_t^3)-U_N(I_9,N)] +$$
$$p_{10}[U_I(I_{10},N)^*(G_t-F_t^3)-U_N(I_{10},N)] = 0. \qquad 3.7$$

In summation notation:

$$H_2 = \sum_{k=1,2} p_k[U_I(I_k,N)^*G_t-U_N(I_k,N)] + \sum_{k=3..10}\sum_{j=1-4} p_k[U_I(I_k,N)^*G_t-F_t^j)-$$
$$U_N(I_k,N)] = 0. \qquad 3.8$$

Comparative Statics

The direct and cross second partial derivatives of the First Order Equations are evaluated to derive second order conditions and comparative statics results.

$H_{11} = \partial E^2(U)/\partial t_1{}^2$. $H_{22} = \partial^2 E(U)/\partial t_2{}^2$. $H_{12} = H_{21} = \partial^2 E(U)/\partial t_2 \partial t_1$.

$$H_{11} = \sum_{\substack{k=1,3,5,\\7,9}} p_k[U_{II}(I_k,N)^*L_t{}^2 - U_{NN}(I_k,N) - 2^*U_{IN}(I_k,N)^*L_t] + \sum_{\substack{k=2,4,6,\\8,10}} p_k[U_{NN}(I_k,N)]. \qquad 3.9$$

$$H_{22} = \sum_{k=1,2} p_k[U_{II}(I_k,N)^*G_t{}^2 - U_{IN}(I_k,N)^*G_t] + \sum_{\substack{k=3..\\10}} \sum_{j=1..4} p_k[U_{II}(I_k,N)^*(G_t-F_tj)^2 - U_{IN}(I_k,N)^*(G_t-F_tj)] + U_{NN}(I_k,N)^*\sum_{\substack{k=1..\\10}} p_k - U_{IN}\,[G_t\sum_{k=1,2} p_k + \sum_{\substack{k=3..\\10}}\sum_{j=1..4} p_k(G_t-F_tj)]. \qquad 3.10$$

$$H_{21} = p_1[U_{II}(I_1,N)^*G_t{}^*L_t + U_{NN}(I_1,N) - U_{IN}(I_1,N)^*(G_t+L_t)] + p_2[U_{NN}(I_2,N) - U_{IN}(I_2,N)^*G_t] + \sum_{\substack{k=3,5,\\7,9}} \sum_{j=1..4} p_k[U_{II}(I_k,N)^*(G_t-F_tj)^*L_t + U_{NN}(I_k,N) - U_{IN}(I_k,N)^*(L_t+G_t-F_tj)] + \sum_{\substack{k=4,6,\\8,10}} \sum_{j=1..4} [U_{NN}(I_k,N) - U_{IN}(I_k,N)^*(G_t-F_tj)]. \qquad 3.11$$

Expressed as a Jacobian matrix equations 3.9 through 3.11 appear as:

$$\mathbf{J} = \begin{matrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{matrix}$$

A maximum requires the determinant of the Jacobian of the first order condition equations to be positive definite or, $H_{11} * H_{22} - H_{21}^2 > 0$.

For any parameter, $t_1, t_2, p_a, p_{c|a}, p_{f|c}, p_{p|c}, p_{pr|c}$, αj, ø, ß, or e, the comparative statics are determined by differentiating the first order equations with respect to the parameter, say ß, and using Cramer's rule to solve the resulting system of equations.

$$\partial H_1/\partial \beta = \partial H_l/\partial t_1 * \partial t_1/\partial \beta + \partial H_1/\partial t_2 * \partial t_2/\partial \beta. \qquad 3.13a$$

$$\partial H_2/\partial \beta = \partial H_2/\partial t_1 * \partial t_1/\partial \beta + \partial H_2/\partial t_2 * \partial t_2/\partial \beta. \qquad 3.13b$$

In matrix form:

$$\begin{bmatrix} \partial H_1/\partial t_1 & \partial H_1/\partial t_2 \\ \partial H_2/\partial t_1 & \partial H_2/\partial t_2 \end{bmatrix} * \begin{bmatrix} \partial t_1/\partial \beta \\ \partial t_2/\partial \beta \end{bmatrix} = \begin{bmatrix} \partial H_1/\partial \beta \\ \partial H_2/\partial \beta \end{bmatrix}$$

or

$$\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix} * \begin{bmatrix} \partial t_1/\partial \beta \\ \partial t_2/\partial \beta \end{bmatrix} = \begin{bmatrix} H_{1\beta} \\ H_{2\beta} \end{bmatrix} \qquad 3.14$$

$$\partial t_1/\partial \beta = 1/|\mathbf{J}|\,[\,H_{1\beta}{*}H_{22} - H_{2\beta}{*}H_{12}]. \qquad 3.15a$$

$$\partial t_2/\partial \beta = 1/|\mathbf{J}|\,[\,H_{11}{*}H_{2\beta} - H_{21}{*}H_{1\beta}]. \qquad 3.15b$$

Ambiguities occur in determining the signs of H_{12}, $H_{1\beta}$, and $H_{2\beta}$. H_{12} appears in both solutions and in fact appears in all comparative static solutions. An inability to resolve ambiguities in H_{12} makes ambiguities in other cross partials moot points. Close scrutiny of H_{12} reveals the sources of the ambiguity.

$$H_{21} = p_1[U_{II}(I_1,N){*}G_t{*}L_t + U_{NN}(I_1,N) - U_{IN}(I_1,N){*}(G_t+L_t)] +$$
$$p_2[U_{NN}(I_2,N) - U_{IN}(I_2,N){*}G_t] + \sum_{\substack{k=3,5,\\7,9}} \sum_{j=1..4} p_k[U_{II}(I_k,N){*}(G_t-F_t^j){*}L_t$$
$$+ U_{NN}(I_k,N) - U_{IN}(I_k,N){*}(L_t+G_t-F_t^j)] +$$

$$\sum_{\substack{k=4,6,\\8,10}} \sum_{j=1..4} [U_{NN}(I_k,N) - U_{IN}(I_k,N)^*(G_t\text{-}F_tj)]. \qquad 3.16$$

All of the p_k's are positive; as are G_t, L_t, and F_tj. For a penalty to be an effective deterrent (G_t-F_tj) is restricted to be positive. Schmidt and Witte (1984) pointed out that the sign of U_{II} can be determined by making assumptions regarding risk preferences. $U_{II} = 0$ if an individual is risk neutral and $U_{II} < 0$ if the person is risk averse. $U_{NN} < 0$ is accepted by assuming the marginal utility of leisure declines with more leisure. U_{IN} measures the change in the marginal utility of leisure with a change in income. No explicit argument has been presented in the literature which provides insight to the direction of the change. If assumed to be positive, then rich individuals value leisure more than poor individuals. Conversely, if $U_{IN} < 0$ then poor individuals value leisure more than rich ones. No evidence conclusively supports either assumption. A third assumption is $U_{IN} = 0$ which means separability between income and leisure in the utility function. If I assumes risk neutrality, i.e. $U_{II} = 0$, and diminishing marginal utility of leisure, ie. $U_{NN} < 0$, then equation 3.16 reduces to 3.17 and H_{21} is unambiguously negative. People are expected to be risk averse, $U_{II} < 0$, rather than risk neutral, but invoking the risk aversion assumption results in an ambiguous sign for H_{21}. The sum of the terms in the first bracket is negative as are the second and fourth terms. The third term is positive which causes the sign of H_{21} to be indeterminant.

$$H_{21} = p_1[U_{II}(I_1,N)^*G_t^*L_t + U_{NN}(I_1,N)] + p_2U_{NN}(I_2,N) +$$
$$\Sigma\Sigma p_k[U_{II}(I_k,N)^*(G_t\text{-}F_tj)^*L_t +$$

$$\sum_{\substack{k=3,5,\\7,9}} \sum_{j=1..4} U_{NN}(I_k,N)] + \sum_{\substack{k=4,6,\\8,10}} p_k U_{NN}(I_k,N). \qquad 3.17$$

The ambiguity is present in other equations. Much attention is given to the effectiveness of increasing the probability of a prison term for convicted criminals, $\partial t_2/\partial p_{p|c}$. This requires the analysis of $\partial H_1/\partial p_{p|c}$ and $\partial H_2/\partial p_{p|c}$.

$$\begin{aligned}\partial H_1/\partial p_{p|c} &= (1-e)^*p_a{}^*p_{c|a}[U_I(I_7,N)^*L_t - U_N(I_7,N)] - \\ &\quad e^*p_a{}^*p_{c|a}U_N(I_8,N) \\ &= p_a{}^*p_{c|a}[U_I(I_7,N)^*L_t - U_N(I_7,N)] - \\ &\quad e^*p_a{}^*p_{c|a}U_I(I_7,N)^*L_t \\ &\quad +e^*p_a{}^*p_{c|a}{}^*[U_N(I_7,N) - U_N(I_8,N)]. \qquad 3.18a\end{aligned}$$

$$\begin{aligned}\partial H_2/\partial p_{p|c} &= (1-e)^*p_a{}^*p_{c|a}[U_I(I_7,N)^*(G_t-F_t{}^3) - U_N(I_7,N)] + \\ &\quad e^*p_a{}^*p_{c|a}[U_I(I_8,N)^*(G_t-F_t{}^3) - U_N(I_8,N)] \\ &= p_a{}^*p_{c|a}[U_I(I_7,N)^*(G_t-F_t{}^3) - U_N(I_7,N)] - \\ &\quad e^*p_a{}^*p_{c|a}[U_I(I_7,N)^*(G_t-F_t{}^3) - U_N(I_7,N)] + \\ &\quad e^*p_a{}^*p_{c|a}[U_I(I_8,N)^*(G_t-F_t{}^3) - U_N(I_8,N)] \\ &= p_a{}^*p_{c|a}[U_I(I_7,N)^*(G_t-F_t{}^3) - U_N(I_7,N)] - \\ &\quad e^*p_a{}^*p_{c|a}[U_I(I_7,N) + U_I(I_8,N)]\,^*(G_t-F_t{}^3) + \\ &\quad e^*p_a{}^*p_{c|a}[\,U_N(I_7,N) - U_N(I_8,N)]. \qquad 3.18b\end{aligned}$$

In equation 3.18a and 3.18b the sign of the final term is ambiguous. The difference measures the change in marginal utility of leisure between two different income levels, I_7 and I_8. As previously argued the sign of this term is indeterminant. An analogous problem existed when determining $\partial t_2/\partial p_{pr|c}$. These ambiguous results and those in H_{21} prohibited any comparison of effectiveness between probation and prison within a theoretical framework.

Unambiguous results are feasible when time entered the decision process only through the budget constraint but at a cost. The models are not as realistic and the results are not intuitively attractive. In general, Heineke (1978) showed this specification of the model is recursive, and that time allocated to legal work is independent of all parameters except the return to labor in legitimate jobs. The individual determines the amount of time to work and then all other allocations are subsequently determined.

The theory does make some contributions. Although the comparative results are ambiguous in realistic models they suggest which variables to include in empirical tests.

Table 3.1

Column 1	Column 2	Column 3
(1) Employed and not arrested	$I_1=W_o+L(t_l,\beta)+G(t_i,\o)$	$p_1=(1-e)(1-p_a)$
(2) Unemployed and not arrested	$I_2=W_o+G(t_i,\o)$	$p_2=e(1-p_a)$
(3) Employed, arrested, but not convicted	$I_3=W_o+L(t_l,\beta)+G(t_i,\o)-F^1(t_i,\alpha)$	$p_3=(1-e)p_a{}^*(1-p_{c\|a})$
(4) Unemployed, arrested, but not convicted	$I_4=W_o+G(t_i,\o)-F^1(t_i,\alpha$	$p_4=ep_a(1-p_{c\|a})$
(5) Employed, arrested, convicted, and fined	$I_5=W_o+L(t_l,\beta)+G(t_i,\o)-F^2(t_i,\alpha^2)$	$p_5=(1-e)^*(p_ap_{c\|a}p_{f\|c})$
(6) Unemployed, arrested, convicted, and fined	$I_6=W_o+G(t_i,\o)-F^2(t_i,\alpha)$	$p_6=ep_ap_{c\|a}p_{f\|c}$
(7) Employed, arrested, convicted, and imprisoned	$I_7=W_o+L(t_l,\beta)+G(t_i,\o)-F^3(t_i,\alpha)$	$p_7=(1-e)p_ap_{c\|a}p_{p\|c}$
(8) Unemployed, arrested, convicted, and imprisoned	$I_8=W_o+G(t_i,\o)-F^3(t_i,\alpha)$	$p_8=ep_ap_{c\|a}p_{p\|c}$
(9) Employed, arrested, convicted, and probation	$I_9=W_o+L(t_l,\beta)+G(t_i,\o)-F^4(t_i,\alpha)$	$p_9=(1-e)p_a{}^*(1-p_{f\|c}-p_{p\|c})$
(10) Unemployed, arrested, convicted, and probation	$I_{10}=W_o+G(t_i,\o)-F^4(t_i,\alpha)$	$p_{10}=ep_a(1-p_{f\|c}-p_{p\|c})$

CHAPTER 4: Data

Sources of the Data

The data originated from different sources within the Harris County (Houston) criminal justice system and the Texas State Board of Pardons and Parole. Computerized criminal histories were available through the Justice Information Management System (JIMS) of Harris County. Most case files contained the "Harris County Pretrial Services Agency Interview Report" and a "Case Review Sheet" as part of a probationer's file. Prison inmates' files contained Parole Review Forms, Certificates of Parole, documentation of prison rule violations, criminal activity of a parolee and other documents with personal background. A statewide and national computer network provided activity of probationers and prison releasees not living in Harris County.

The JIMS system contained information on any case filed in Harris County courts. Data was organized by individual offender which facilitated easy tracking of previous and subsequent criminal activity relative to the 1980 offense. Included, were the offense and date of each case, the court which heard the case, the disposition of the case, and the eventual outcome of the punishment, ie. if probation was the sentence the success or failure of completing probation was noted. The birth date, sex, physical characteristics, and address were also available. Occasionally, employment information was available but this was generally incomplete, outdated, and unreliable.

The Pretrial Services Agency Interview Sheet duplicated some information but did have unique personal information. The questionnaire provided marital status, number of children, attorney of record, employment conditions, income level, previous employer, current address, how long at current address, and length of time in the county. This survey was the principle source of economic data of an individual. Each time a person was arrested Pretrial Services interviewed the defendant and provided an update of personal statistics.

Probationers' files held by the Adult Probation Department was another source of personal information. The "Case Review Sheet" provided the educational level and an indicated any drug or alcohol dependency of probationers.

Prison inmates, like probationers, responded to entrance queries. Criminal histories were recorded with personal data similar to that found in the JIMS files or the Pretrial questionnaire. Educational attainment for defendants sent to prison was noted in these documents.

Data unique to prison inmates was contained in other sources. Pre-parole reviews registered the trusteeship level attained, educational courses completed, the number of furloughs, current marital status, the length of prison time accumulated, and a recommendation for or opposition to parole. "Conditions of Parole" delineated where and with whom the prospective parolee lived, employment prospects, fees paid and the frequency of contacts with the parole officer. The "Certificate of Parole" designated whether the releasee was supervised or unsupervised. Separate documents detailed the occurrence of rule violations while incarcerated.

Deterrence was measured by the monthly average of the number of officers on patrol and the monthly average of the arrest rate during a person's time at risk. The averages were calculated from data compiled by the Houston Police Department.

The data used to calculate the monthly average of unemployment rates in the Houston SMSA while a person was at risk were from the Texas Employment Commission.

General Characteristics of the Data

The data consisted of 838 felony offenders convicted in Harris County, (Houston) Texas during the months of January and February 1980. Five-hundred forty-six received probated sentences and 292 received prison sentences. Of the prison inmates, 212 were released by June 30, 1986. Missing data eliminated 14 probationers and 4 ex-inmates from the study which reduced the final sample to 740 observations.

January and February were representative months for the six months previous and six months subsequent to the start of the study. No elections occurred to precipitate changes in bench membership.

Harris County, located in Southeast Texas, had a population of approximately 2.5 million people.

Criminal Justice Characteristics

In addition to descriptive statistics relevant to the full sample, variables were compared across sanction types. Standard Chi-square analysis of contingency tables and a comparison of means of criminal and socio-economic variables across the two populations were performed. Hochberg's method was used to compare means because the sample sizes were unequal. The descriptive statistics have been displayed in Table 4.1.

The most logical source of differences between probationers and prisoners was in the criminal justice variables. The nature of the offense often determined whether a convicted offender was sent to prison or was placed on probation. Presumably probationers were convicted of relatively less serious offenses. Some offenses mandated a prison term. For summary purposes, twenty-eight offense categories were consolidated into four types - personal injury, theft, drug related, and lesser felony. Included in the theft group was robbery of a person. Although robbery was defined by law as a theft, or an attempted theft, accompanied with a threat or occurrence of personal injury the original intent was for the transfer of income and/or property and thus robbery was grouped with other theft offenses. Offenses related to drugs and drug use were probably underrepresented. Many burglaries and other theft oriented crimes were committed to support drug addictions. The data did not distinguish between theft offenses which supported a drug habit and theft offenses for other reasons.

Sixty percent of the offenses were theft related. Personal injury offenses and drug related offenses comprised 16.22% and 12.97% of the total respectively. The remaining 10.68% was attributed to lesser felony offenses. Of the 445 theft cases, 327 (73.48%) were probationers. The category of personal injury crimes contained the greatest percentage of offenders sent to prison. One hundred and twenty cases involved personal injury offenses and 69 (57.72%) of them resulted in the defendant serving a prison term. Eighty-one of the 96 drug offenders were placed on probation while the remaining15 were sent to prison. Seventy-nine offenders were accused of a lesser felony offense and 73 (92.59%) were placed on probation.

A similar trend was apparent in the composition of each sanction type. Only 6 (2.88%) of offenders sentenced to prison were convicted of a lesser felony offense. Nearly 14% of the probationers committed the similar type of crime. The proportion of probationers who were drug offenders was more than twice the proportion of prison inmates who were drug offenders, 15.22% versus 7.21% respectively. Both groups had a majority of theft offenders in their population. Sixty-one percent of the probationers were theft offenders and 56.67% of the prison population were convicted of theft. Only 9.59% of probationers were convicted of personal injury crimes. This was significantly below the 33.17% of prison inmates convicted of similar offenses. The Chi-square statistic calculated to test the relationship between sanction and type of crime was 79.47, with one degree of freedom. The null hypothesis of no relationship was rejected at the 5% level.

The presence, length and seriousness of ones criminal history were often instrumental in determining a sanction. A first time offender was more likely placed on probation than an offender with numerous previous criminal convictions. Texas law required imprisonment for some offenses committed by repeat offenders. Forty-five percent of the study population had a criminal history. Seventy-five percent of offenders sent to prison had a criminal history. First time offenders dominated probationers. Only 32.27% of probationers had any prior criminal convictions. The Chi-square statistic calculated to test the relationship between the sanction and the presence of prior criminal activities was 107.12 with one degree of freedom. This was significant at the 5% level.

The number of prior convictions was a measure of the length of a criminal career. The average number of prior offenses was 0.81 and the maximum was 6. Probationers averaged 0.55 prior convictions and inmates averaged 1.47 prior convictions. The difference between the average number of prior convictions of the respective groups was statistically significant at the 5% level. The severity of the prior convictions, i.e. felony versus misdemeanor, measured the seriousness of the career. Of the 156 prison inmates who had prior convictions, 136 (87.18%) had felony convictions.

Conversely, 83 (46.89%) of the probationers who had prior convictions had prior felony convictions. Offenders sent to prison had a longer and a more serious criminal background than those placed on probation.

Some offenders were confined to jail until their case was tried. Other offenders were released via 1 of 5 different pretrial release agreements. For the full sample, 311 (42.03%) awaited trial under a bond agreement. Fifty-three percent of the probationers were released on bail but only 13.94% of offenders who eventually went to prison were released on a pretrial agreement. The average length of pretrial jail time was 16.8 days. Even those defendants who were eventually released on bond had some jail time but the probationers' average was 25% of the averate for offenders sent to prison. Probationers waited an average of 9.5 days while prison inmates spent an average of 35.7 days in jail waiting for their trial. A significantly greater number of eventual probationers awaited trial out in society than did eventual inmates.

Other criminal justice and case resolution characteristics included the type of attorney representation, type of trial, and who imposed sentence. Neither group had a majority which retained their own attorney. Court appointed attorneys represented 458 (61.89%) of the defendants. Probationers retained an attorney in 42.86% of the cases and 26.96% of inmates retained their own counsel.

The dominant form of resolving a case was via plea bargaining. Eighty-six percent of the cases were resolved this way while the remainder were resolved in the courts. Eighty-eight percent of the probationers and 80.77% of the inmates were convicted through the plea bargaining process. The proportions of probationers and inmates tried by a jury were 4.51% and 16.35%, respectively. Of all offenders, 719 (97.16%) were sentenced by a judge. A judge imposed sanctions on probationers and inmates 98.50% and 93.75% of the time respectively.

Socio-economic Characteristics

A comparison of socio-economic variables highlighted the differences between probationers and inmates. The sample population was predominantly male with 86 (11.61%) female offenders. Only 13 (6.13%) of the prison inmates were women while 73 (13.74%) of probationers were women. The difference between these proportions was significant at the 5% level and implied women were more likely to receive probation than to receive prison sentences.

The sample average age was 25 years. The difference in average ages between the two groups was not significant. Probationers were, on average, 25 years and 2 months and prison inmates averaged 25 years and 3 months.

Nearly 50% of the group was white. Thirty-eight percent of the offenders were black and 12% were Hispanic. Blacks were disproportionately represented relative to their percentage of the general population of the county, 19.6%. The proportion of Hispanics was more closely in line with the percentage of the general population.

The 280 whites which received probation comprised 52.63% of all probationers and 76.29% of whites. The 87 whites which received prison sentences comprised 41.83% of all offenders sent to prison and 23.71% of whites. Blacks made up a significantly greater proportion of prison inmates than they did probationers. They comprised 46.63% of offenders sent to prison and 34.59% of those placed on probation. These proportions were significantly different at the 5% level. As a group, 65.48% of all blacks received probation. The percentages for Hispanics were much closer to equality. Hispanics comprised 11.06% of the prison inmates and 12.78% of probationers. Differences were revealed when the Hispanic population was divided by the type of sanction. Approximately 75% of Hispanics were probationers and 35.27% were prison inmates. This data showed an overrepresentation of blacks, relative to the general population, in both the percentage of all offenders and in the percentage of offenders sent to prison. On the basis of race alone, the risk of going to prison was greatest for black offenders. Hispanics faced the second greatest risk, and white offenders faced the least risk of going to prison.

Only 23.65% of the group was married and relatively more probationers were married than those who went to prison. Married probationers, 133, comprised 23.12% of all probationers while married inmates, 42, comprised 20.19% of their respective group.

The low percentage of married offenders could have contributed to the low average number of children. The overall average number of children was 0.66. Probationers averaged 0.7 children and prison inmates averaged 0.5 children.

The average years of education for the population was 10 years 6 months. The group averages differed by five months - 10 years 8 months for probationers versus 10 years 3 months for inmates. In absolute terms the difference between the means appeared minor but it was statistically significant.

Geographical stability, measured by the amount of time in the county, was common to both groups. Overall, 66.76% of the offenders had been residents of Harris county for five or more years. Offenders sentenced to prison comprised a larger proportion, 70.67%, than probationers, 65.41%. This stability assisted in the follow-up process. Probationers remained in the area and prison inmates returned to the county upon release from prison.

Drug and alcohol abuse were often cited as causes of crime. Addiction to one or both of these substances was a problem for 239 (32.30%) of the full sample. It was less of a problem for offenders placed on probation, 130 (24.44%), than for offenders sent to prison, 109 (52.40%).

Economic variables indicated differences in opportunities between the groups. Income and employment affected the ability to retain an attorney rather than accept court appointed counsel. Income measured the opportunity cost of future criminal activity. The majority of offenders were employed, 61.62%, and 3.30% of them received some form of welfare. Employment status was only part of the picture. The average monthly income reported was $552, or $6624 per year. Probationers were relatively more likely to be employed and earn a greater income than offenders sent to prison. Sixty-five percent of the probationers held jobs and earned an average of $604 per month while 52.40% of the inmates were employed and earned an average of $420 per month.

The overwhelming majority of all offenders were male and were an average of 25 years of age. Most were single and the average number of children for both groups was less than one. Both the average probationer and average inmate had less than a high school education. Probationers were slightly better educated than prison inmates. There was a predominance of long term residents. Every ethnic group had a majority of its members as probationers but the ethnic mix within the prison or probation population does not reflect societal norms. Blacks were over represented and whites were underrepresented in the prison population, and the converse was true in the probation population. Addiction to drugs or alcohol was more common among prison inmates than among probationers. Finally, the group as a whole was relatively poor with a high rate of unemployment. Probationers were more likely to be employed than inmates and had a relatively greater income.

Table 4.1

Descriptive Statistics

Variable	Population	Probationers	Inmates
N	740	532	208
Offense type:			
Lesser Felony	79	73	6
Drug	96	81	15
Theft	445	327	118
Personal Injury	120	51	69
Criminal History:			
Prior Convictions	333	177	156
Prior Felony Conv.	219	83	136
Ave. No. of Priors	0.81	0.55	1.47
Pretrial Release	311	282	29
Ave. Jaildays	16.8	9.5	35.7
Retained Attorney	282	228	54
Type of Trial:			
Plea Bargain	636	468	168
Judge	47	40	7
Jury	58	24	34

Table 4.1 (continued)

Variable	Population	Probationers	Inmates
Sentenced By:			
Judge	719	524	195
Jury	21	8	13
Sex:			
Male	654	459	195
Female	86	73	13
Race:			
White	367	280	87
Black	281	184	97
Hispanic	91	68	23
Ave. Age	25y	25y2m	25y3m
Married	175	133	42
Education	10.66 yr.	10.90 yr.	10.33 yr.
Length of Resid.	13.1 yr.	12.5 yr.	14.75yr.
Long-term Resid.	495	348	147
Drug/Alcohol Habit	239	130	109

CHAPTER 5: STATISTICAL METHODOLOGY

The primary motivation for developing any theory of criminal behavior was to determine which variables at society's disposal could be expected to modify deviant behavior. Knowledge of the criminal choice process was a fundamental initial step toward effective criminal justice policies. Chapter 3 demonstrated the difficulties involved in deriving comparative static results within a modestly realistic model of crime. The development of such a model did have merit. It was able to indicate which factors influenced the decision-making process of a criminal. The most salient outcome was that legal and illegal time allocations were reached simultaneously. In addition to its counterpart, each was a function of all parameters which influenced any source of income or the costs of crime. Although the theory was unable to clearly discern the most effective policy variables, it was able to suggest which factors to include in empirical models.

Knowledge of which variables to include did not assure availability of data. Measurement problems have been standard in the research of the economics of crime. Legal employment time was relatively easy to obtain. The Department of Commerce routinely collected the number of hours worked by persons for the calculation of employment statistics. The number of hours devoted to crime was more difficult to ascertain. A typical criminal was unlikely to keep a precise log of his or her time.

In lieu of an exact measure, numerous proxies have been substituted. Studies which were based upon personal interviews used the subject's estimate of time or the number of crimes to which the subject would confess. A greater number of crimes committed were expected to require a greater number of hours allocated to illegal activities. Criminal justice records were also used to measure individual criminal activity. Numerous sources, eg. police and court records, were available within a criminal justice system. An extensive criminal record was expected to reflect an extensive allocation of time to crime.

Both proxies, individual interview and criminal justice records, contained measurement error. A personal interview would not have revealed crimes the individual had committed but to which the individual had not confessed. The reasons could have been as simple as the offender forgetting a minor offense or an offense deemed not serious enough to mention. Conversely, an individual may have been hesitant to mention a serious crime for which he had not been suspected. Criminal justice records had measurement error because they contained only crimes for which an individual had been arrested. This underrepresented true criminal activity in 2 ways. Reported crimes for which arrests were never made or charges never filed were not represented in the anyone's record. Unreported crimes caused official records to underrepresent the actual criminal activity. To reconcile these shortcomings it was generally assumed that the individual who allocated a relatively large portion of the time to crime would admit to relatively more crimes in a personal interview and would have a relatively more extensive police record than a person who allocated a relatively small portion of time to crime.

Dichotomous measures of criminal activity were also quite common. If, during the study period, an individual was arrested and/or convicted of a crime the person was considered a failure and the indicator of criminal activity had a value of 1. If a person had remained criminally inactive the indicator had a value of 0. This measure had the same problems with regard to missing committed crimes and was inferior for another reason. Information was lost by recording only the presence or absence of criminal activity. A person with numerous crimes was categorized the same as a person with a single offense. The degree of activity was completely lost which made a dichotomous measure the weakest of proxies for amount of time allocated to illegal activities.

The measure of time allocated to crime in this dissertation originated from criminal justice records but was different than the measures previously discussed. Here, criminal activity was measured by the duration of time between the initial, or instant, offense and the recidivating offense. The recidivating offense was the first offense for which an individual was arrested and subsequently convicted following the instant offense. It was assumed that the more time an individual devoted to crime the more likely it was the person would be arrested and convicted and this would occur in a shorter period of time than a person who allocated relatively fewer hours to illegal activities. For example a driver who exceeded the speed limit infrequently was likely to drive for a longer duration without receiving a speeding ticket than a driver who routinely exceeded the speed limit. This measure had the potential for measurement error for the same reasons given above plus an additional reason. A professional criminal may have been proficient enough to avoid detection for a substantially longer period of time than someone of lesser experience. This measure indicated the professional to be a law abiding citizen for a longer period than the inexperienced criminal who was arrested and convicted after only a short duration. The measure admittedly missed some criminal acts and likely overestimated the duration between criminal acts.

Duration Analysis

Measuring criminal activity as the duration between crimes required the use of statistical methods particularly designed for the analysis of duration data. Duration data measured the time between two events, in this situation the time between an offender's release and the first arrest that lead to a conviction. This duration was known as the "time at risk." The beginning of one individual's duration period needed not coincide with another's. Offenders were arrested over a two month period and had a staggered entry into the study. Some cases were not resolved in the same month in which they were initiated and offenders sent to prison obviously had a lagged entry. If an offender recidivated, the time at risk concluded upon the arrest date of the recidivating offense that subsequently lead to a conviction. If the person did not recidivate, the duration ended at the termination of the study. It should be clear that duration times were measured in months and that it was possible for individuals to have the same duration times but different intervals of months. No time at risk commenced previous to January 1, 1980 nor extended beyond June 30, 1986.

The variation in the duration times generated a distribution which was characterized by being truncated at zero and usually had a significant proportion of the sample with duration times close to zero in length. The distribution was truncated at zero because everyone was at risk some positive time interval before they recidivated. People who recidivated within two weeks of release were defined to have a duration of zero months. This itself did not present a problem. The distribution of many economic variables have a non-negativity constraint. Aggregate supply of goods and services were restricted to be positive. Wages and salaries and the resulting distribution of income were defined as non-negative values. The difference between these distributions and the distribution of duration times was the relative frequency of observations that had values equal or nearly equal to zero. With respect to aggregate supply and income distributions, a zero value was located at the extreme end of the left tail of the distribution and had a relative frequency of nearly zero. Consequently, these values contributed essentially nothing to the solution of any problem which was analyzed using the respective distribution. Conversely, for a distribution of times at risk it was quite common for the relative frequencies of values close to zero to be quite high. In fact, it was often the case that the greatest relative frequencies clustered near zero and relative frequencies declined as the duration periods lengthened.

To explain the variation among the times at risk a mathematical density function which approximated the actual distribution was needed. The most commonly used distribution in early applications was the exponential. The greatest relative frequency occurred at zero and declined at a constant rate moving away from zero. Other distributions applied were the Weibull, of which the exponential was a special case, the lognormal, and the log-logistic. These distributions were attractive because all were truncated on the left and restricted the argument of the function to be equal to or greater than zero. These distributions, rather than the Standard Normal, were employed in empirical models designed to determine which factors best explained the variation in the duration times.

Many offenders were still at risk at the end of the study. The actual duration for these offenders was unknown. Some may have recidivated the day after the cutoff date and some may never recidivate. In either case the duration time was defined as censored. If censoring occurred, standard linear regression produced biased and inconsistent parametric estimates.

Assume the regression model $y_i = X_i'\beta + \mu_i$. If censoring was present then for some y_i's, $y_i > T$ where T was a known point and for that observation $\mu_i > T - X_i'\beta$. The standard assumption was $E(\mu) = 0$ but in this case $E(\mu_i | y_i > T) = E(\mu_i | \mu_i > T - X_i'\beta)$. $E(\mu_i)$ did not equal zero and depended on X_i when $y_i > T$. This situation violated one of the standard assumptions of the classical regression model and produced biased and inconsistent results.

The temptation was to simply discard the censored observations. This was paramount to discarding information and would reduce the efficiency of the estimates and also would preclude the opportunity of comparing groups with common times at risk but with different outcomes. Another temptation was to define failure times for the censored observations equal to the time at risk. This introduced erroneous information and again prevented comparison across groups. It was essential to recognize the presence of censoring and accommodate that presence using duration data analysis techniques.

The previous paragraphs have alluded to the advantages of using duration analysis over other approaches. Principally, more information was made available. The timing of failure was explicitly modeled only within duration models. The traditional dichotomous (yes/no) ignored the timing information. Duration models differentiated between quick recidivists and those who recidivated after lengthy periods and those offenders who never recidivated. The increased information lead directly to more efficient results and policy recommendations.

Duration data allowed the focus of the analysis to change from the dichotomous measure of failure or success to the continuous measure of time until failure. More specifically, the probability of surviving beyond a particular month at risk and the probability of failing during a particular month could be estimated. Duration time, T, was assumed to be continuous, non-negative, and random. The distribution of T was estimated by one of three fundamental functions - the survival function, the density function and the hazard function.

The survivor function measured the probability that T would be greater than some specified amount of time t. Mathematically the general functional form was given as:

$$F(t) = pr(T \geq t) \;,\; t \;\; (0,\infty). \qquad 4.1$$

F(t) was a monotone, nonincreasing left continuous function such that F(0)=1 and lim F(t)=0 as $t \longrightarrow \infty$.

The probability density function measured the probability that someone would fail during period t and was given as:

$$f(t) = \frac{-dF(t)}{dt} = \lim_{\Delta \to \infty} \frac{pr(t \leq T \leq t+\Delta)}{\Delta}. \qquad 4.2$$

It was based on the total number of observation initially in the study.

The hazard, or age specific failure rate, measured the conditional probability of recidivating during time t given that the individual had not recidivated up to period t. Mathematically, it measured the change in the slope of the survival function relative to the passage of time. It was given as

$$h(t) = \frac{f(t)}{F(t)} = \frac{-d \ \ln F(t)}{dt} = \lim_{\Delta \to 0+} \frac{pr(t \le T < t+\Delta | t \le T)}{\Delta} \quad . \qquad 4.3$$

The hazard estimated the probability of failure in a particular period based on the number of observations at risk at the beginning of the period.

By $h(t) = -d\ln F(t)/dt$ and $F(0) = 1$, $F(t)$ can be expressed in terms of the hazard as

$$F(t) = \exp(-\int^{t} h(u)du) = \exp[-H(t)], \qquad 4.4$$

where $H(t)$ was the integrated hazard function which measured the accumulated failure probabilities over time.

If the failure times were assumed to follow a specific parametric distribution, the survival, density, and hazard functions were written respectively as $F(t,\varnothing)$, $f(t,\varnothing)$, $h(t,\varnothing)$ and $H(t,\varnothing)$.

Maximum likelihood estimation techniques were used to estimate the parameters. The likelihood function, written to accommodate censoring, was a product of the survival function and the density function.

If L represented the likelihood function then

$$L = \pi f(t_i,\varnothing)^{1-c} * F(t_i,\varnothing)^{c}. \qquad 4.5$$

If the duration for an observation was uncensored, a recidivist, then c had the value of 0 and the likelihood function estimated the probability of the individual failing in period t. If the duration for an observation was censored, a nonrecidivist, then c equaled 1 and the likelihood function estimated the probability of the person surviving beyond period t.

The likelihood function was separable into the recidivists and nonrecidivists and 4.5 could be rewritten as 4.6.

$$L = \pi_u f(t_i,\emptyset)^* \ \pi_c \ F(t_i,\emptyset). \qquad 4.6$$

The subscript u indicated the failure times and the subscript c indicated the censored times.

Most often it was the log of the likelihood function which was estimated. It appeared as

$$l = \Sigma_u \log f(t_i,\emptyset) + \Sigma_c \log F(t_i,\emptyset). \qquad 4.7$$

Because $f(t_i,\emptyset) = h(t_i,\emptyset)^*F(t_i,\emptyset)$ and $F(t_i,\emptyset) = \exp[-H(t_i,\emptyset)]$, 4.7 could be rewritten as

$$\begin{aligned} l &= \Sigma_u \log h(t_i,\emptyset)^*F(t_i,\emptyset) + \Sigma_c \log F(t_i,\emptyset) \\ &= \Sigma_u \log h(t_i,\emptyset) + \Sigma_u \log F(t_i,\emptyset) + \Sigma_c \log F(t_i,\emptyset) \\ &= \Sigma_u \log h(t_i,\emptyset) + \Sigma \log F(t_i,\emptyset) \\ &= \Sigma_u \log h(t_i,\emptyset) - \Sigma H(t_i,\emptyset). \qquad 4.8 \end{aligned}$$

The derivation showed the fundamental importance of the hazard function in duration analysis. It was usually the hazard function that attracted the most interest. Cox and Oakes (1984) listed several reasons why the hazard held such an interest. Computationally, hazards were often the most convenient functions when censoring was present. Comparisons across groups of individuals were most easily accomplished using the hazard function. From a policy perspective it was of interest to know the chance of failure of an individual currently at risk, the chance of failure relative to other points in time, and what treatment programs affected the hazard of failure.

It was quite common to develop and test models in which survival was a function of independent variables. Models, known as accelerated failure time models, assumed a baseline distribution and the independent variables were said to act upon the baseline distribution. The baseline distribution was relevant for individuals in which $\mathbf{x} = 0$. The effect of an independent variable was multiplicative on failure time and either accelerated or decelerated an individual's time to failure.

Let $\exp(\mathbf{x}'\boldsymbol{\beta})$ be the scalar multiple and T_0 be the duration from the baseline distribution for an individual with $\mathbf{x} = 0$. An individual with $\mathbf{x} \neq 0$ had a duration $T = \exp(\mathbf{x}'\boldsymbol{\beta})^*T_0$. This was transformed into a log linear model by taking the log of T and getting

$$y = \mathbf{x}'\boldsymbol{\beta} + y_0, \qquad 4.9$$

where $y = \log(T)$ and y_0 was the $\log(T_0)$ which acted as the error term with the assumed baseline distribution. $\boldsymbol{\beta}_i$ of the estimated parameter vector $\boldsymbol{\beta}$ gave the percentage difference in the time to failure between a person with $\mathbf{x} = 0$ and an individual for which $x_i \neq 0$.

Commonly used distributions included the Weibull, the exponential, and the log-logistic. The exponential was the simplest in form and had a constant hazard rate. Its survival function and hazard functions were respectively $F(t) = \exp(-\lambda t)$ and $h(t) = \lambda$. The constant hazard rate meant the probability of someone failing was invariant to the amount of time the person had been at risk. Its simplicity was attractive for computional purposes but the constant hazard rate was not realistic for ex-offenders. Intuition suggested the probability of recidivating was dependent upon the amount of time the person had been at risk.

The Weibull function was a generalization of the exponential and allowed for a time dependent hazard rate. The Weibull survival function was $F(t) = \exp[-(\lambda t)^p]$. The hazard function was $h(t) = \lambda p(\lambda t)^{p-1}$. If $p = 1$ the Weibull hazard reduced to the exponential and if $p < 1$ the hazard was monotone decreasing. This specification more closely reflected the expected behavior of an offender's hazard rate over time.

If the baseline distribution was log-logistic then T_0 had the logistic density

$$\frac{\exp(T)}{(1+\exp(T))^2}.$$

The survivor function and hazard function of the log-logistic, like the exponential and the Weibull, were relatively simple algebraic expressions. They were respectively

$$F(t) = \frac{1}{1+(\lambda t)^p} \quad \text{and} \quad h(t) = \frac{\lambda p(\lambda t)^{p-1}}{1+(\lambda t)^p}.$$

If $p < 1$ the hazard was monotone decreasing from ∞ and was monotone decreasing from λ if $p = 1$. If $p > 1$ then the hazard was 0 at time zero, rose to a maximum and then decreased toward 0 over time.

The proportional hazard model was an alternative to the accelerated failure time models. The proportional hazard model assumed that the ratio of the hazard rates of two individuals was constant over time which made specification of the distribution of failure times unnecessary. Both absolute rates may change over time but they change at the same rate to maintain the constant proportionality.

Individual i's hazard can be expressed as the product of some scalar constant and the baseline hazard.

$h_i(t,x) = \psi(x,\beta)^* h_o(t)$, where $\psi(x,\beta)$ was some scalar function and by definition $\psi(x=0) = 1$. The function $h_o(t)$ was the baseline hazard function with an unspecified distribution.

Cox (1972) developed the proportional hazard model and partial likelihood estimation which calculated the likelihood of an individual failing in a particular period conditional on the set at risk at the beginning of the period. This conditional probability was given as

$$\frac{h_i(t_j)}{\sum_{k\in R(\rho_j)} h_k(\rho)} = \frac{\psi(i)}{\sum_{k\in R(\rho_j)} \psi(k)}. \qquad 4.10$$

This method used only information regarding the order of failure, or censoring, to calculate likelihoods. The baseline hazard function which related the hazard to time was cancelled in the algebraic calculations and thus information regarding the timing of failure was not used. $\acute{I}(x,\beta)$ was commonly parameterized as $\acute{I}(x,\beta)=\exp(x\beta)$. This produced less efficient estimates but Efron (1977) showed the loss was too small for concern.

Changes in the hazard rate with respect to time was defined as duration dependence. It was said to exist if $dh(t)/dt \neq 0$. Positive duration was present if $dh(t)/dt > 0$ and negative duration was present if $dh(t)/dt < 0$. Intuition indicated that the hazard function for most offenders exhibited negative duration dependence. Part of the reason was in state dependency. The longer someone was in a particular state the less likely a move from that state would occur. The longer a drug addict was able to remain drug free the less likely the person would return to drug usage. The longer someone remained criminally inactive the less likely the person would recidivate.

Another source of negative duration dependency was heterogeneity among the people at risk. Some people may have been more prone toward criminal behavior for one or more reasons. These people had a relatively greater hazard than others in the early periods. When they failed early, they left behind the offenders with relatively lower hazards and consequently the average hazard rate declined giving the appearance of negative duration dependency.

Heterogeneity was both observed and unobserved. Observed heterogeneity was reflected in educational levels, income opportunities, criminal background, family background, etc. Unobserved heterogeneity was measured by attitudes toward risk, childhood experiences and self-esteem.

If unobserved heterogeneity existed it caused the estimates of covariate effects and duration effects to change across different specifications or distributions of failure times. Although there are formal ways to handle the problem, it was not possible to implement them at this stage of the research. I assumed unobserved heterogeneity was a secondary order effect.

Model Specification

Conventional econometric models contain both structural and reduced form equations. This was not typical in the field of duration analysis. The models estimated in this dissertation were single equation reduced form models. They were technically correct but did not estimate the relationship between the time allocated to legal and time allocated to illegal activities. That required a simultaneous equations model.

Methods necessary to estimate a simultaneous hazard model have only recently been proposed in the theoretical literature. I hope in future research to implement these theoretical estimators.

CHAPTER 6: RESULTS AND POLICY RECOMMENDATIONS

Probability of Sanction

A single equation logit model was used to estimate the affect of different offender circumstances on the sanction choice. The dependent variable, SANCTION, was zero for probationers and one for prison inmates. The covariates which were expected to explain the variation of imposed sanctions have been listed and explained in Table 6.1.

The imposed sanction could be levied from 1 of 4 sources. Many offenders were sentenced via a plea bargain agreement, while others were sentenced by a judge or a jury. The sanction could also have been prescribed by law such as requiring a person with numerous offenses to be incarcerated. Consequently, the covariates TRIAL, FELON, AND PRIORS were included in the model. TRIAL denoted whether a judge or jury sentenced the offender or if the offender was sentenced through a plea bargain. A value of 1 indicated the case had been tried in court. Zero indicated a plea bargain arrangement. The sign of the estimated coefficient of TRIAL was expected to be negative. The probability of probation relative to the probability of prison was less for offenders who were sentenced by a judge or jury than for offenders who reached a plea bargain agreement. FELON indicated the presence of prior felony convictions. FELON equaled 1 for offenders who had prior felony convictions and 0 for other offenders. Prior felony convictions were expected to reduce the probability of probation relative to the probability of incarceration. The total number of all prior convictions was represented by PRIORS. This measure included both misdemeanor and felony convictions. Offenders with an extensive criminal history were expected to have a lower probability of probation relative to the probability of prison.

The severity of the crime often disqualified a person for probation. Likewise, some minor offenses would not have been punished with imprisonment. For these reasons, the offenders were categorized into 4 different groups by offense type. PERSNINJ was assigned a value of 1 for those convicted of a personal injury offense and 0 if not. DRUG equaled 1 for drug offenders and THEFT equaled 1 if the person was convicted of a theft related offense. For offenders convicted of other types of felonies the values for all of the previously mentioned variables were 0.

The dummy variable FELON indicated whether someone had previously been convicted of a felony offense. The variable PRIORS measured the actual number of previous crimes for which an individual had been convicted. PRIORS was an indicator of the extensiveness of a person's criminal history and FELON was an indicator of the seriousness of the history.

All offenders received legal counsel; either privately retained or court appointed. RETATTNY had a value of 1 if the respective attorney was retained and 0 otherwise.

Upon arrest offenders were arraigned and bond status was determined. A judge, not necessarily the judge who eventually heard the case, established the worthiness of the defendant to remain free while awaiting trial. The evaluation included the person's likelihood to be available on the court date and to remain criminally inactive in the interim. The dummy variable MADEBOND indicated whether the person made bond or remained in jail during the pre-trial period. People who awaited trial in jail may not have been able to pay the bail bond amount because of their income or because the bond amount was intentionally set high for any income level reflecting the severity of the crime.

Demographic variables included race indicators, BLACK, HISPANIC, and OTHRACE, a sex indicator SEX, and employment indicator, EMPLOYED. These variables addressed issues regarding racial composition, sex differences, and employment status across sanctions.

The estimated coefficients, displayed in Table 6.2, measured the change in the probability of a person being supervised on probation relative to the probability of being incarcerated.

MADEBOND was significant at the 1% level. A person who was released on bond was 183.62% more likely to be placed on probation than someone who failed to make bond. This strongly implied the bond system was an excellent predictor of who eventually was sent to prison.

PERSNINJ, FELON, PRIORS, BLACK, and EMPLOYED were all significant at the 5% level and An offender convicted of a personal injury crime was 286.33% less likely to receive probation than someone convicted of a minor felony offense. A unit increase in the number of prior convictions reduced the chance for probation versus prison by 89.26%. People with a criminal past were likely former probationers and were not given second and third chances. Offenders with previous felony convictions reduced their chances of probation relative to prison by 168.84%. Offenders with relatively extensive and serious criminal pasts were much less likely to receive probation than to be sent to the Texas Department of Corrections.Employment increased the chance of probation over prison by 58.01%. A job indicated stability and opportunity cost of future crimes. The probability of receiving probation relative to the probability of being sent to prison was 42.73% less for blacks than it was for whites. This was the only race in this sample that was significant at any standard confidence level.

RETATTNY, TRIAL, and THEFT were significant at the 10% level. The coefficient for RETATTNY was opposite the expected sign. People who retained an attorney were 48.16% less likely to be placed on probation than sent to prison. This may have reflected the significant proportion of offenders who "pleaded out" to receive probation on the advise of a court appointed attorney. This was borne out by the sign of coefficient for TRIAL. A person whose case went before a judge or jury was 51.15% less likely to receive probation than prison. The incentive to plea bargain with a court appointed attorney was apparent. Finally, offenders convicted of theft crimes reduced their chance of probation relative to prison by 87.47%.

The estimated logit coefficients indicated the change in the probability of probation relative to the probability of prison. They were also used in the logistic probability function to estimate the absolute probability of an individual, with particular characteristics, of being placed on probation. These probabilities were estimated using variables significant at the 5% level and variables significant at the 10% level. The logistic probability function was given as:

$$\text{Prob(probation)} = \frac{1}{1 + \exp(-(x\beta))}.$$

where x is the vector of characteristics which describe the individual and β is the logit estimates.

The type of person who was most likely to be placed on probation was an employed white first time offender who had committed a non-personal injury offense and had made bail. That type of person had an estimated 99.64% of being placed on probation. A black in the same economic and criminal circumstances had a 99.43% estimated probability of probation.

A minor criminal past and employment status had negligible effects upon the estimated probability of probation. An employed, white, non-personal injury offender with minor previous convictions had an estimated probability of 99.09%. The black counterpart had an estimated probability of 98.59%. Similar offenders who were unemployed but had no criminal past were 99.35% and 98.99% certain of probation respectively.

Personal injury offenses, serious criminal backgrounds and failure to make bail significantly reduced an offender's chance for probation. The offender least likely to receive probation was the unemployed black who had committed a personal injury offense, who had previous felony convictions, and who was not released on bail. That type of offender had a 6.08% chance of probation. The white counterpart had a 9.20% chance.

The expanded model which included variables significant at the 10% level produced similar results. An employed, white, first time offender who committed an offense other than a personal injury offense or a theft offense, who made bond, used a court appointed attorney to plea bargain the case had a 99.64% chance of being placed on probation. The offender least likely to be placed on probation was an unemployed black repeat offender who had committed a personal injury offense and retained an attorney for a trial. That criminal type had a 2.31% chance of probation.

The probability of probation for other offender types ranged between those extremes. Generally, the more serious the offense and the more extensive the history the lower was the probability of being placed on probation. Blacks had overall lower probabilities for probation than whites. An employed white repeat offender convicted of a theft offense who did not make bail had a 57.88% probability of probation. A black in similar circumstances had a 46.72% chance of probation. A similar white offender who had committed a personal injury offense, rather than a theft offense, had only a 15.33% chance for probation. This probability was nearly

50% larger than the 10.36% chance for probation for a black in a similar situation. For offenders who committed other than personal injury or theft offenses the chances for probation increased. An employed white repeat offender who did not make bond had a 76.30% chance for probation. The similar black offender had a 67.27% chance for probation.

These results indicated that the most likely offender to be placed on probation were the employed white first time offenders who were convicted of drug related or minor felony offenses and were able to await their court date on bail. Unemployed black repeat offenders who had committed a personal injury or theft offense and had not made bond were almost certainly sent to prison.

Duration Analysis

The determination of sanctions was only one issue. Another issue was which factors explained the variation of duration times for probationers and what factors explained the variation of duration times for inmates. The situation of a probationer was fundamentally different from the situation of a prisoner upon release. Probationers immediately returned to society, possibly remained employed, and also likely retained their family relationship. If they were unemployed, they could immediately start looking for employment. Their continued presence in society enabled them to minimize any loss in labor skills. Alternatively, prisoners left society. Any employment ended and family relationships likely changed. Inmates who were incarcerated for a number of years may have found, upon release, they had fallen behind relative to probationers and non-criminals with respect to job skills.

To reflect the differences in the respective situations after release, the data was partitioned by sanction and then respective models were estimated for each group using relevant variables. For example, the amount of time a probationer was on probation did not apply to ex-inmates. Analogously, the amount of time a person was incarcerated did not apply to a probationer. The educational level at the time of the initial arrest was relevant for probationers but the educational level at the time of release from prison was the relevant covariate for ex-prisoners. School attendance was mandatory for any prisoner who had not achieved an eighth grade education but courses up through college were available for anyone who wanted to continue their education.

The accelerated failure time model was used under different assumptions about the distribution of duration times. Four different distributions were tested - the Weibull, the exponential, the lognormal, and log-logistic. Accelerated failure time estimates were generated using maximum likelihood techniques. Only the exponential model fit the data differently from the other three and it fit the data the least effectively. Results produced by the Weibull model were used because the proportional hazard rate was easily computed directly from the Weibull model by dividing the accelerated failure time coefficient by the negative of the extreme value scale parameter. Results have been presented in terms of hazard rates and the accelerated failure time coefficients, evaluated at the probationers' mean time at risk.

Factors Which Affect Probationers

The probation model contained covariates, defined in Table 6.3, which were relevant at the time of the initial offense. To estimate the affect of these different offense types PERSON, DRUG and THEFT were included. An offender convicted of a personal injury offense and placed on probation was expected to have a greater hazard of failing than someone convicted of a minor felony offense. They were expected to be less inhibited in committing another offense, than an offender who committed only a minor infraction. People convicted of selling or possessing drugs were expected to quickly continue their way of life. They were also expected to have a greater hazard rate than minor felony offenders. Theft offenders were expected to be more likely to fail than minor offenders because some used this type of crime as a vocation.

PRIOR and FELON were included to represent a person's criminal past and the seriousness of the past. Offenders with the more serious and extensive pasts were expected to be at a greater risk of failure.

HABIT represented the status of a person's drug or alcohol addiction. If the person had a problem then HABIT equaled 1. This variable may have contained measure error. The information originated from interviews conducted at the outset of the offender's sentence. A common characteristic of addiction was self denial and as such some offenders likely lied when asked about drug or alcohol problems. Nevertheless, offenders with drug or alcohol problems were expected to be at a greater risk of failure than offenders without problems.

The expected effect of the amount of time on probation, MOP, was ambiguous. If probation was a rehabilitative process then the length of time on probation was expected to reduce the hazard of recidivating. If, the functional mission of the probation department was surveillance, then the longer an offender was on probation the greater the probability of being detected of some criminal activity. The length of time on probation and hazard of failing would have been positively related.

DAYNJAIL, the number of days a person spent in the city or county jail prior to the trial, was included. Jailtime was anticipated to reduce the hazard of a probationer failing. The conditions of jail and the treatment received while in jail were expected to inform the potential probationer of one component of the personal cost of the crime. This information served two purposes. The probationer better evaluated this component of the cost of crime and the time in jail could also have been used as a proxy for conditions in prison, a possible destination for future convictions.

A person's educational level was expected to influence the decision to recidivate. Those with greater educational achievement had greater alternative legal opportunities and were expected to be at a lower risk of failure than those with lower educational levels and fewer legal opportunities. IEDUCATN was the number of years of schooling completed by the probationer.

Income from legal work was anticipated to deter an individual from returning to crime. Income was the opportunity cost of unsuccessful crime activity. The greater the income the more the probationer put at risk by recidivating. MNTHPAY measured the dollar amount of monthly income the probationer reported on the pre-trial questionnaire.

Employment status was considered to have a separate effect from income. A legitimate occupation required time away from criminal activities. The more hours a person worked during a day the fewer hours were available for criminal activity. It was possible for someone to "moonlight" in criminal activities but generally it was anticipated that people with jobs had a lower hazard rate than the unemployed. EMPLOYED was 0 for the unemployed and 1 for the employed.

Other socio-economic variables which were expected to influence the timing of failure were sex, age, marital status and the number of children for which the person was responsible. GENDER was 0 for women and 1 for men. AGE was the age of the person at the time of the initial offense and INITKIDS was the number of children. MS was a dichotomous variable, equal to 0 if the offender was not married and 1 if the person was married. Men were expected to be at a higher risk of failure than women primarily because of the disproportionate number of men involved in crime. The other three variables were expected to reduce the hazard rate. All three were some measure of maturity or responsibility of an individual. Maturity was expected to cause the individual to better evaluate the correlation between criminal behavior and consequences of the behavior. Added responsibility for others increased the opportunity cost of future crimes.

A race variable was included to test for ethnic differences in the decision to return to crime. Minorities, with relatively fewer opportunities, were anticipated to return to crime relatively sooner than whites. These were the same categorical variables, BLACK and HISPANIC, defined previously in the logit analysis.

General deterrence was measured by AVECOP, the monthly average of the number of officers on patrol in Houston during a person's time at risk, and AVEARR, the police department's monthly average arrest rate during a person's time at risk. The arrest rate was calculated by the number of arrests per reported crimes. AVECOP was a measure of the size of the police force and AVEARR was a measure of the productivity of the police force. An increase in the number of officers was expected to be apparent to the criminal community and reduce overall criminal activity. This would, at the individual level, reduce the hazard of failing for a probationer. Increased productivity, measured by the monthly arrest rate, was expected to increase the hazard of an individual failing. Given a police force size, an increase in the ability to solve crimes and make arrests was expected to increase the risk of failing.

AVEEMP, the average monthly unemployment rate in the Houston SMSA while the person was at risk, was another aggregate covariate. It was included to indicate the general activity of the economy and the relative income position of offenders. The general activity of the economy was expected to affect the hazard of recidivating. If unemployment was relatively high fewer citizens moved among markets and more citizens remained at home. The decline in activity reduced the pool of potential victims available to criminals. Contemporaneously, fewer residences were unattended for long periods of time. Cantor and Land (1985) argued a declining economy effected both criminal motivation and criminal opportunities.

An additional effect from a changing economy was a change in the criminal's perceived relative welfare. If a person's utility was dependent upon his relative income position in society then utility could be affected by the general economic activity. This notion was the basis of the Relative Income Hypothesis. Applied to the criminal choice paradigm, a person's utility was a function of the perceived relative welfare in society. Danzinger and Wheeler (1975) used interdependent utility functions and relative deprivation to explain the rising crime rates in the expanding economy of the 1960's and the low crime rates during the depression of the 1930's. Good and Pirog-Good (1987) found that a deficit between expectations of individual's welfare and the actual welfare position led to greater criminality. Within this framework it was expected that the aggregate unemployment rate would have a negative effect on the hazard rate.

The estimated hazard rates for the probationers have been displayed in Table 6.4. The initial model for probationers contained 19 covariates which were expected to influence the time to failure. Six of the coefficients were significant at the 10% confidence level. The final specification was developed by keeping all of the significant covariates from the initial model as well as some covariates that were insignificant in my model but had been found significant by other authors. Some categories were changed. Drug offenders were consolidated with "Others" which changed the number of types of crimes committed from 4 to 3 with drug and others being the control group. PERSON and THEFT remained as dichotomous variables. Hispanics were grouped with whites and only BLACK was included as a race variable. MNTHPAY, IEDUCATN, AGE, and INITKIDS were removed from the model.

The value of the likelihood function of the final specification was not significantly different than the initial specification. The likelihood ratio test result was 1.713 with 6 degrees of freedom. The variables that were significant previously were still significant and some variables gained significance.

The seriousness of a person's criminal history was significant, as before. A person who had committed felony crimes in the past was 0.59% more likely to fail than a person who was not a former felon. PRIOR, which measured criminal history, was significant at the 12% level, an improvement over the initial model, but continued to have the wrong sign. It indicated a person with prior convictions of any kind was less likely to fail than a first time offender.

HABIT was significant but its sign was opposite the expected. The hazard of failing for an addict was 0.30% less than non-addicts. One explanation was that admitted addicts received drug counseling and had more contact hours with a probation officer than non-addicts. Each probationer was evaluated for supervision needs which the probation department used to determine the number of officer contact hours per month. An addict was evaluated to have relatively greater needs than a similar probationer with no addiction problem and was required to be counseled more frequently. This greater contact reduced the hazard of failure for addicts.

MOP was also significant. Offenders on probation for 6 months had a 0.01% less chance of failing than offenders on probation for five months. This result indicated probation performed a rehabilitative role rather than a surveillance role.

AVECOP was a significant deterrent. An 10% increase in the monthly average of officers reduced the hazard of someone recidivating by 0.224%.

AVEARR was significant and had a positive sign. A 10% increase in the arrest rate increased the hazard of a probationer failing by 0.219%. In comparison to AVECOP, improvements in investigatory resources were less productive than increments to the police force.

AVEEMP was significant and indicated a 1 percentage point increase in the monthly unemployment rate decreased the hazard of recidivating by 2.43%. This supported the relative deprivation and the reduced criminal opportunities hypotheses.

BLACK, which had not been significant before, was significant in the final specification. The sign was opposite expectations. Blacks were 0.24% less likely than non-blacks to recidivate. Blacks may have had social situations which required more supervision and counseling.

The effects of the covariates were also measured in terms of the expected change in the time until a probationer failed. These effects, measured in terms of months, were estimated by multiplying the accelerated failure time coefficient by the mean time at risk. A covariate that had a positive proportional hazard rate decreased the average time to failure. The estimates have been entered in Table 6.5.

A probationer who had previous felony convictions was likely to fail approximately 10 months earlier than the the probationer who had no felony criminal history.

A probationer with an alcohol or drug habit was expected to be successful approximately 5 months longer than the probationer who did not have an addiction problem.

The influence of a month of probationary supervision was to increase the duration period by one week. This meant an additional year of supervision could be expected to post-pone failure by 3 months.

A 10% increase in AVEARR decreased the time to failure by 3.8 months and an equivalent increase in AVECOP extended the duration by 3.9 months. In terms of months the effects were nearly equal but in opposite directions. Improvements in investigatory methods lead to more arrests and the greater number of officers on the street lead to greater visibility and deterred potential recidivists.

The unemployment rate had a large effect on the time to failure. An increase of 1 percentage point in the unemployment rate increased the duration by over 42 months.

Blacks were expected to remain criminally inactive slightly more than 4 months longer than whites.

From a policy perspective, probation services reduced the hazard of a person recidivating. The type of crime made no difference but the amount of time the person was supervised did make a difference. A case could be made to increase the length of time felony offenders were required to be on probation. The impact of increasing the police force and increasing the productivity of the force were both beneficial in reducing crime, with increments in productivity more effective. The person who likely responded best to probation was a black probationer with no previous felony convictions, had a drug or alcohol addiction and received counseling and rehabilitation.

Factors Which Affect Prison Inmates

For the same reasons given in the previous section the Weibull model was used. Some variables unique to probationers were excluded from the prison model. MOP and DAYNJAIL were dropped. The time in the county jail was expected to have no significant effect on offenders who ultimately went to prison. MNTHPAY and EMPLOYED were also dropped because they reflected conditions at the time of the initial offense and were not relevant for post prison circumstances. The covariates used in the prison model have been defined in Table 6.6.

Some variables common to both groups were measured at different time in the offenders life. PRISONMS reflected the marital status of the inmate upon release from prison. MS measured the marital status of a probationer at the time of the case. AGERELS was the age of the inmate upon release. The probation model contained the probationer's age at the time of the offense.

Variables unique to prison inmates were introduced. PRISTIME measured the number of months an inmate was incarcerated. Two opposing effects were possible from time in prison. The deterrent effect was expected to influence the individual once released. The longer someone was in prison the greater the cost of the crime. The isolation from family and society and loss of freedom was expected to cause the individual to lead a crime free life upon release.

The other effect was the prisonization effect. Prisonization occurred to inmates who became conditioned to prison life to the degree that coping in free society was more difficult after prison than before. Job responsibilities of an inmate often did not reflect the opportunities available in society at large and labor skills of an inmate often diminished. Jobs available within prison were frequently jobs in society that were at the bottom of the pay scale. Another source of prisonization was the regimentation of the day. The inmate made very few decisions with regard to allocation of time. Daily activities were predetermined and the inmate needed only to follow the directions of the prison guards. Upon release, the regimentation was removed and the ex-inmate needed to make decisions about time allocation. Decision making capabilities needed to be redeveloped to cope in society.

Extensive amounts of time in prison reduced the network of non-criminal friends and expanded the group of criminal friends. Upon release it was easier to look up friends known from prison rather than start new friendships or rekindle old ones. Aggravating the problem was the reluctance of law abiding citizens to associate with convicted felons.

These reasons made the adjustment to free society as a law-abiding citizen difficult and the return to crime relatively less difficult. If the prisonization effect dominated the deterrent effect then the coefficient was expected to be positive, the length of time in prison increased the hazard of failing after release.

PPERLIFE was the percent of a person's life the current term in prison had consumed. It was expected that the larger the proportion of one's life that had been spent as an inmate the larger the hazard of failure afterwards and that a prison sentence would be more effective on someone who was relatively young. The older offender knew the system and the routine. The percent of one's life that had been spent in prison was not available so the ratio of the amount of time in prison for the current offense to the person's age was used as a proxy. For example, the older of 2 inmates with the same prison terms was expected to have a higher hazard rate.

Many ex-inmates were released to society without any previous arrangements for a residence. Some ex-inmates were required to live in a halfway house for a specified amount of time after release. Other releasees had previous arrangements to live with parents or other family members. The adjustment to society was expected to be affected by the living arrangements. A person who lived alone did not have the support system that was available to persons who lived in a halfway house or with family. As a resident of a halfway house, the ex-inmate was required to follow rules, meet job search requirements, and report to a supervisor. Ex-inmates who were released on their own usually were required to report to a parole officer but were not supervised as closely as a resident of a halfway house. Offenders who lived with their family after release had the support of relatives and other loved ones. The family had the potential of providing employment information and a relatively stable home environment. HALFWAY and FAMILY were dichotomous variables which indicated the living arrangements of the offender. A value of one indicated the respective arrangement. Both were equal to zero for individuals who lived alone. Offenders who lived in a halfway house or with their familes were expected to have a lower hazard of failure than those that lived alone after release.

An inmate who entered prison with less than an eighth grade education was required to attend school. EDMPROVE, a dichotomous variable, indicated the inmate enrolled in educational programs in excess of those required. EDMPROVE replaced IEDUCATN as a measure of educational achievement. EMPLRELS indicated the employment status upon release. Fewer than 5% of the exiting prisoners reported any income they would be earning and consequently a measure for income was unavailable.

Five coefficients were significant at the 5% confidence level in the initial prison model . AVECOP and AVEARR and AVEEMP were significant and had the same signs as their counterpart in the probation model. HALFWAY and FAMILY were significant and both reduced the hazard rate of failing relative to living alone upon release.

The final specification contained 15 variables, six of which were significant at the 5% confidence level. The hazard rates for the initial and final specifications have been presented in Table 6.7.

PRISTIME, which was not significant in the initial model, was significant in the final specification. Each additional month of incarceration increased the hazard of failing by 0.04%. The results indicated the prisonization effect dominated the deterrent effect. This was not to imply prison terms did not have a deterrent effect, only that the counter effect of prisonization was dominant. The longer someone remained in prison the greater the hazard that the person would fail again after released.

AVEARR was significant and positive. This was the same effect found with probationers. A striking difference was found between the relative sizes of the coefficient across groups. An increase in the number of officers on the street was 4 times more effective in deterring probationers than ex-inmates. The type of criminal who was sent to prison was not as easily deterred as the type who was placed on probation.

An 10% increase in the productivity of the police force increased the hazard of failure for an ex-inmate by only 0.06%. This was significant but the absolute size was quite small. A comparable increase in AVEARR increased the hazard of probationers by 0.22%. Productivity gains were apparently aimed at detecting the relatively more inexperienced criminals. Substantial increases in criminal investigation methods were required to place experienced criminals at greater risk of failure.

AVEEMP was significant and indicated support for the arguments presented for the probationers. As in the previous 2 variables, ex-inmates were not effected as much by changes in this variable as were probationers. A 1% increase in the unemployment rate reduced the hazard of failure for an ex-inmate by 1.19%. The smaller value was attributed to the position of the ex-inmate in society. They likely felt more alienated from society than did probationers and required a greater decline in the economy to increase their welfare. Consequently, serious criminals were not as easily deterred as probationers.

The coefficients of HALFWAY and FAMILY indicated those inmates released to halfway houses or to family members had a better chance of succeeding. The hazard of failure declined 1.21% and 1.58% respectively relative to those that lived alone. This supported the expectation that post-incarceration assistance was beneficial.

The effect of covariates on the time to failure was also estimated for the prison group. The mean time to failure for ex-inmates, 28.29 months, was used to calculate the estimates.

A one month increase in the prison sentence was expected to cause the ex-inmate to fail 3 weeks sooner than an inmate released one month earlier.

The effects of AVEARR and AVECOP on the time to failure for ex-inmates were analogous to the effects on probationer but not as large. A 10% increase in the productivity of the police force reduced the time to failure for ex-inmates by approximately 1 month. An equivalent increase in the average number of officers on the street lengthened the duration by slightly less than a month.

A 1 percentage point increase in the unemployment rate increased the duration period by 20 months. This magnitude was unexpected.

The benefit of the halfway houses and families was evident. An ex-inmate released to a halfway house or a family member remained criminally inactive 21 and 27 months respectively longer than an individual who was released without such arrangements.

The inmate most likely to succeed generally spent less than the average amount of time in prison and was released to a halfway house or a family member. This person had the necessary support to help make a successful adjustment to post-prison life. The ex-inmate had a lower risk of failure in periods of police force expansion and improvements in crime solving techniques. An improvement in the urban economy lead to an increased hazard rate.

Although an increase in the size of the police force was a deterrent it was not as effective as with the typical probationer. Productivity improvements within the police force were also relatively less effective with ex-inmates than probationers. Typical ex-inmates were more hardened criminals than probationers and thus improvements in police protection needed to be more pronounced to attain an equivalent response from ex-inmates. Ex-inmates' hazard rates were also less sensitive than probationers' rates to changes in the urban economy. A declining economy which had fewer potential victims at large and fewer homes unattended did not deter ex-inmates as much as probationers from recidivating. The ex-inmates had fewer alternative opportunities and were not deterred as much by residents in their homes.

My results were in agreement with previous work of some others but disagreed with others. Direct comparisons of many authors were not possible because relatively few researchers have used duration analysis to compare the effectiveness of sanctions.

Stollmach and Harris (1974) found prison inmates released to halfway houses remained criminally inactive longer than those who were simply released into society. Schmidt and Witte (1987) found lengthy prison terms contributed to shorter time to failure. They also found, as I found, education did not play a significant role in explaining the variation in the time to failure.

Contrary to my findings, Schmidt and Witte did find drug and alcohol abuse problems contributed to an earlier failure time for ex-inmates. I found no significant impact for drugs and alcohol. They found black were likely to return sooner and I found blacks were likely to recidivate later than whites.

Policy Prescriptions

Some factors and characteristics that were significant predictors of sanctions were not significant factors in explaining the distribution of durations for either probationers or for ex-inmates. The use of a court appointed attorney and a person's bail status were two significant factors that were relevant at the time of the trial but were not relevant once the offender was back in society.

The type of crime was useful in predicting which offenders were sent to prison and which were placed on probation but it was not significant in determining the hazard of failing after release - regardless of the sanction.

Blacks were more likely than whites to be sent to prison but the hazard rate for black ex-inmates, was not different from whites ex-inmates. Black probationers however were expected to remain criminally inactive longer than white probationers.

The person's employment status was significant at sentencing but it was not explicitly significant in determining the hazard. Some factors that may have influenced employment were significant in affecting the hazard rate.

Some factors explained the sanction received and the time to failure rate. Prior felony convictions, FELON, increased the probability of being sent to prison. Probationers who were repeat felony offenders had an increased hazard of failing than probationers who had no felony history. Ex-inmates who had previous felony convictions were no more at risk than ex-inmates with no felony past.

Generally, the instruments used to determine sanctions were not useful in assessing the probability of success and the factors that affected success were not always known at the time of sentencing. Even so some policy recommendations were possible with respect to sentencing. The results of the duration analysis for probationers showed the length of time under supervision decreased the hazard of failure. There was an apparent rehabilitative effect of the sanction. Consideration should be given to increasing the length of time on probation. An increase in the number of months on probation would reduce the overall hazard of probationers failing.

Admitted drug addicts and alcoholics on probation had a lower hazard rate than general probationers. This was attributed to the increased counseling and supervision received by these probationers. It is likely not all addicts admitted their problem and received the needed treatment. Sentences for all felony probationers that required enrollment in rehabilitative programs would decrease the average failure rate of probationers.

Judges and juries had more discretion when imposing probation than prison. A prison sentence was usually within limits of a specified amount of time. Once the offender was in prison, activities within prison and conditions upon release were not within their jurisdiction. This research found that the time in prison did not rehabilitate nor serve as a deterrent. The longer an offender was incarcerated the greater the hazard of failing after release. For prison inmates, any positive effects which decreased the hazard were outweighed by the negative effects of incarcerations. Essentially, prison was a way station. The short run benefit of a prison sentence was the removal of the criminal from society. Unfortunately, the longer society was protected in the short run the more likely it would be violated in the long run.

Options to decrease the hazard after an inmate was released were found among the results. The more support an ex-inmate had the lower was the risk of failure. The support was measured by with whom the releasee lived. Ex-inmates who lived either in halfway houses or with family and friends were significantly less likely to fail than those that reentered society alone. These arrangements facilitated the transition to life in mainstream society and possibly offset some of the negative effects of life in prison. The results predicted a decline in overall hazard rates if prospective releasees were required by parole boards to accept residence at a halfway house when arrangements were not possible with relatives.

Three variables exogenous to the courts, probation department, and correctional institutions were also found to be significant in changing the hazard rate. Increased productivity of the police department and a larger police force increased and decreased the hazard respectively. The general economic activity and the hazard rate were positively related. Crime declined in periods of slower economic growth.

Some policy recommendations came from understanding the relationship between economic activity and the hazard rate. It was during economic expansions when the "pickings were ripe" that the hazard increased. The accessibility of victims and the perceived relative decline in welfare were inducements to recidivating. A greater effort in job training was needed to ensure that ex-offenders could overcome labor market hurdles especially during periods of strong economic growth. The results suggested it was unwise to assume that all levels of labor would share equally in economic growth.

These results produced some recommendations that could reduce the cost of crime. During the sentencing phase it was found blacks were more likely to be sent to prison than whites. It was also found that blacks on probation were likely to remain criminally inactive longer than whites on probation. The group most likely to do best on probation was the group least likely to be place on probation. A need to re-evaluate sentencing policies was apparent. It was suggested to extend the length of probation and require closer supervision. The composition of prison sentences need to be changed. The length of time people were incarcerated should be reduced but the time of post-release supervision needed to be structured to allow the inmate a gradual transition into society. The improved supervision of both groups should have included job training and aggressive attempts to place the individuals upon completion of the training.

Table 6.1

Variables Included in Logit Analysis

Variable	Description
SANCTION	Zero for offenders placed on probation and one for offenders sent to prison.
RETATTNY	Offender retained own attorney. Value of one if defendant retained attorney, zero if represented by public defender.
CITIZEN	One if offender was a U.S. citizen, zero if not.
TRIAL	One if case was resolved by trial and zero if the case was resolved via plea bargain.
PERSON	One if the offense was a personal injury crime, zero if not.
DRUG	One if the offense was a drug related crime, zero if not.
THEFT	One if the offense was a theft related crime, zero if not.
BLACK	One if the offender was black, zero if not.
HISPANIC	One if the offender was hispanic, zero if not.
OTHRACE	One if the offender was not black, hispanic or white, zero if not.
SEX	Zero for women and one for men.
EMPLOYED	One if the offender was employed and zero if the offender was unemployed.
FELON	One if the offender had previous felony convictions, zero otherwise.

Table 6.1 (continued)

PRIORS	One if the offender had any previous convictions, zero otherwise.
MADEBOND	One if the offender was released on bond, zero if not released.

Table 6.2

Logit Estimates for Relative Probability of Probation versus Prison

Intercept	3.1894 (0.9242)
RETATTNY	-0.4904** (0.3023)
CITIZEN	0.0422 (0.6635)
TRIAL	-0.5164** (0.2955)
PERSON	-2.8783* (0.5339)
DRUG	-0.4802 (0.5880)
THEFT	-0.8516** (0.4934)
BLACK	-0.4490* (0.2302)
HISPANIC	-0.2742 (0.3987)
OTHRACE	-16.6347 (736.161)
SEX	-0.4862 (0.4038)
EMPLOYED	0.5802* (0.2198)
FELON	-1.6893* (0.3250)
PRIORS	-0.9110* (0.3325)

Table 6.2 (continued)

MADEBOND	1.8409* (0.3196)

Standard error of estimate in parentheses.

* Significant at the 5% level.

** Significant at the 10% level.

Table 6.3

Explanatory Variables for Accelerated Failure Time Model (Probationers)

PERSON	One if probationer convicted of personal injury offense, zero otherwise.
THEFT	One if probationer convicted of theft offense, zero otherwise.
DRUG	One if probationer convicted of drug offense,zero otherwise.
PRIOR	One if probationer had previous prior convictions of any severity, zero if no prior convictions.
FELON	One if probationer had previous felony convictions, zero if no prior felony convictions.
HABIT	One if probationer had an alcohol or drug abuse habit, zero otherwise.
MOP	Number of months a probationer was supervised on probation.
DAYNJAIL	Number of days spent in jail before the probationer was sentenced.
AVEARR	Monthly average arrest per reported crime during the probationer's time at risk.
AVECOP	Monthly average number of police officers on patrol during the probationer's time at risk.
AVEEMP	Monthly average unemployment rate during the probationer's time at risk.

Table 6.3 (continued)

BLACK	One if the probationer was black, zero otherwise.
MS	One if the probationer was married, zero otherwise.
SEX	One for men and zero for women.
MNTHPAY	Monthly income of the probationer. In dollars.
EMPLOYED	One if the probationer was employed, zero otherwise.
IEDUCATN	Probationer's completed years of school.
INITKIDS	Probationer's number of children.
AGE	The age of the probationer.

Table 6.4
Estimated Hazard Rates for Probation Model
Weibull Distribution

	Initial Specification	Final Specification
Intercept	15.4788	15.4259
PERSON	0.4020	0.3238
THEFT	0.1269	0.0316
DRUG	0.2344	
PRIOR	0.1189	-0.1437
FELON	0.5302	0.5921*
HABIT	0.2972	-0.2996*
MOP	-0.0147*	-0.0147*
DAYNJAIL	0.0040	-0.0041
AVEARR	0.0220*	0.0219*
AVECOP	-0.0225*	-0.0224*
AVEEMP	-2.4355*	-2.4347*
BLACK	-0.2149	-0.2361**
MS	0.1384	0.1313
SEX	0.1363	0.1350
MNTHPAY	0.00002	
EMPLOYED	-0.1170	
IEDUCATN	0.0040	
INITKIDS	-0.0161	
AGE	-0.0032	
SCALE	0.3234	0.3234

* Significant at the 5% level.
** Significant at the 10% level.

Table 6.5
Estimated Effect on Failure Time for
Probation Model
Weibull Distribution

	Initial Specification	Final Specification
Intercept	-269.66	-268.75
PERSON	-7.00	-5.64
THEFT	-2.10	-0.55
DRUG	-4.08	
PRIOR	-2.07	2.50
FELON	-9.24*	-10.32*
HABIT	-5.18*	5.22*
MOP	0.25*	0.26*
DAYNJAIL	-0.07	-0.07
AVEARR	-0.38*	-0.38*
AVECOP	0.01*	0.39*
AVEEMP	42.43*	42.42*
BLACK	3.74	4.11**
MS	-2.41	-2.29
SEX	-2.37	-2.36
MNTHPAY	-0.0004	
EMPLOYED	2.04	
IEDUCATN	-0.07	
INITKIDS	-0.01	
AGE	0.06	

Estimates are evaluated at the mean failure time (53.87 months).
* Significant at the 5% level.
** Significant at the 10% level.

Table 6.6

Explanatory Variables for Accelerated Failure Time Model
(Prison Inmates)

PERSON	One if inmate convicted of personal injury offense, zero otherwise.
THEFT	One if inmate convicted of theft offense, zero otherwise.
DRUG	One if inmate convicted of drug offense, zero otherwise.
PRIOR	One if inmate had previous prior convictions of any severity, zero if no prior convictions.
FELON	One if inmate had previous felony convictions, zero if no prior felony convictions.
HABIT	One if inmate had an alcohol or drug abuse habit, zero otherwise.
PRISTIME	Number of months an inmate was incarerated for 1980 offense.
PPERLIFE	Percent of inmate's life 1980 sentence comprised.
AVEARR	Monthly average arrest per reported crime during the inmate's time at risk.
AVECOP	Monthly average number of police officers on patrol during the inmate's time at risk.
AVEEMP	Monthly average unemployment rate during the inmate's time at risk.
BLACK	One if the inmate was black, zero otherwise.

Table 6.6 (continued)

PRISONMS	One if the inmate was married, zero otherwise.
SEX	One for men and zero for women.
HALFWAY	One for inmates released to the supervision of a halfway house, zero otherwise.
FAMILY	One for inmates who lived with an immediate family member upon release, zero otherwise.
EMPLRELS	One if the inmate was employed upon release, zero otherwise.
EDMPROVE	One if the inmate voluntarily enrolled in educational classes while incarcerated.
KIDS	Inmate's number of children.
AGERELS	The age of the inmate upon release.

Table 6.7
Estimated Hazard Rates for Prison Model
Weibull Distribution

	Initial Specification	Final Specification
Intercept	-7.9084	-8.0087
PERSON	-0.0731	-0.1005
THEFT	0.4824	0.4192
DRUG	0.0818	
PRIOR	0.1373	0.1318
FELON	-0.1938	-0.2071
HABIT	0.1486	0.1523
PRISTIME	0.0426	0.0431*
PPERLIFE	0.1000	0.0866
AVEARR	0.0063*	0.0063*
AVECOP	-0.0050*	-0.0051*
AVEEMP	-1.1922*	-1.1889*
BLACK	-0.2274	-0.2149
PRISONMS	-0.0602	-0.0206
SEX	0.3707	0.3926
HALFWAY	-1.2428*	-1.2092*
FAMILY	-1.6246*	-1.5831*
EMPLRELS	-0.0364	
EDMPROVE	-0.0621	
KIDS	0.0720	
AGERELS	-0.0044	
SCALE	0.6034	0.6033

* Significant at the 5% level.
** Significant at the 10% level.

Table 6.8
Estimated Effect on Failure Time for
Prison Model
Weibull Distribution

	Initial Specification	Final Specification
Intercept	-135.00	-136.71
PERSON	1.25	1.72
THEFT	- 8.23	-7.16
DRUG	-1.40	
PRIOR	-2.34	-2.25
FELON	3.31	3.54
HABIT	-2.54	-2.60
PRISTIME	-0.73*	-0.74*
PPERLIFE	-1.71	-1.48
AVEARR	-0.11*	-0.11*
AVECOP	0.09*	0.09*
AVEEMP	20.35*	20.26*
BLACK	3.88	3.67
PRISONMS	1.03	0.35
SEX	-6.33	-6.70
HALFWAY	21.21*	20.64*
FAMILY	27.73*	27.02*
EMPLRELS	0.62	
EDMPROVE	1.06	
KIDS	-0.04	
AGERELS	0.08	

Estimates are evaluated at the mean failure time (28.29 months).
* Significant at the 5% level.
** Significant at the 10% level.

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