September 1988

TARGETING
SERIOUS AND REPETITIVE OFFENDERS:

THE EFFECT OF CRIME CONTROL LEGISLATION IN ARIZONA

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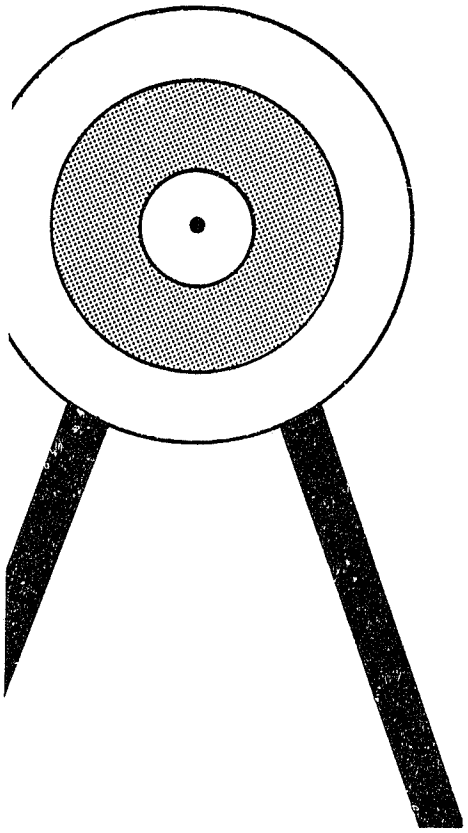

ARIZONA DEPARTMENT OF PUBLIC SAFETY
Information Analysis Section
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Arizona Department of Public Safety
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Ralph T. Milstead, Colonel
Director

by

Barbara C. Nienstedt
James E. Riggs
Thomas Epperlein

September 1988

This research was conducted under grant
87-BJ-CX-K026 from the U.S. Department of
Justice/Bureau of Justice Statistics.

118135

U.S. Department of Justice
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TARGETING SERIOUS AND REPETITIVE OFFENDERS: THE EFFECT OF CRIME CONTROL LEGISLATION IN ARIZONA

EXECUTIVE SUMMARY

The enactment of Section 13-604.01 into Arizona law was heralded as a means to punish dangerous and repetitive offenders by requiring mandatory, consecutive sentences for those convicted of a new crime while on supervised release. This law also mandated that those offenders on supervised release who were convicted of a new, dangerous offense would serve a flat twenty-five calendar years prior to release.

The primary objective of this research was to determine how prosecutors and courts adapted to the requirements of A.R.S. 13-604.01 and whether these actions resulted in keeping with the spirit of the law and with the intent of the law to deter and incapacitate habitual criminals. Using existing OBTS-type data, time-series ARIMA models and probit regression models were developed to examine effects of the new policy. The findings of the research may be summarized as follows:

- Before the new law, plea bargaining from the original charges to the final disposition charges occurred in 58.1 percent of the cases. After the law, there was an increase in all types of plea bargaining for targeted offenders, but a decrease for non-targeted offenders. The incidence of plea bargains for dangerous offenders increased by 178.3 percent.

- The most likely offender to plea bargain was not on probation (i.e., supervised release), or was considered dangerous. Neither race, type of attorney, nor age were significant variables in whether a person plea bargained or not.

- While there was a significant increase in the incidence of plea bargaining, there was little change in plea-bargaining patterns after the new law.

- Private attorneys tended to plea bargain to a greater degree than did public defenders before the law, but did not do so after the law. Clients of public defenders, moreover, tended to receive more prison sentences (and longer ones) than did those of private attorneys. The law did not appear to change these patterns, except that before the law there were no significant differences in sentence lengths.

- Those offenders on probation were not plea bargaining except in the reduction from dangerous to non-dangerous offense status. The time-series analyses also uncovered evidence that offenders on probation bargained to have the offense felony class reduced more often after the new law became effective.

- Both probation sentence lengths and prison sentence lengths were significantly longer after the law. Offenders were also more likely to go to prison.

- The new law did not produce an impact on the number of felony case dispositions.

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STATEMENT OF THE PROBLEM

Since the mid 1970's, crime control policies across the nation have increasingly shifted away from a rehabilitative model to more punitive and retributive forms. At the heart of this shift are two central concepts: just deserts and deterrence.

The former position states that criminals should be penalized to a degree fitting their crimes; an eye for an eye, so to speak. Deterrence is based on the proposition that future crimes may be prevented depending on the punishments meted to those who are apprehended and convicted.

Deterrence theory relies upon the theoretically equivalent components of certainty, celerity, and severity (see e.g., Zimring and Hawkins, 1973: Andenaes, 1974; Blumstein et al., 1978) to produce the desired effect. That is, if the chances that an offender will be apprehended are very good, and if apprehension and adjudication occur closely in time with the offense, and if the sanction for the offense is severe enough, then criminal behavior will be deterred.

Due in part to inadequate evaluation methods and analytical models, most deterrence research and crime control policy evaluation has tested for the effects of certainty or severity (see e.g., Tittle and Rowe, 1974; Grasmick and Bryjak, 1980; Epperlein, 1987) and has not dealt sufficiently with celerity, or with the possible interactions among the three. Nor have these studies dealt adequately with how the adjudication process adapts to maintain an optimum flow of offenders (i.e., celerity) through the system.

Arizona, like many other states, has been faced with increasing crime rates, incarceration rates, and the costs associated with these increases for over a decade. Also like many other states, the Arizona legislature has, since 1974, adopted stricter and more punitive crime policies.

In 1974, mandatory sentences for armed robbery with a gun and possession of narcotics for sale were introduced. The State's prison population climbed rapidly following this policy change, from slightly more than 2,000 inmates at the end of 1974 to over 3,000 inmates by mid 1978. Ironically, though, reported crimes also increased over the same period.

In 1977, the Arizona Criminal Code Commission introduced the concept of presumptive sentencing, modified by "mitigating" and "aggravating" factors, and with increasing sentence severity based on the offender's prior criminal history (repetitiveness) and the degree of physical harm (dangerousness) surrounding the offense. These concepts were codified within a revamped criminal code passed during the 1978 legislative session and effective for all crimes committed on or after October 1, 1978. In this case, prison population did not grow very rapidly immediately following enactment, but did grow steadily until early 1981.

From 1981 until the present, prison population has exploded; by mid 1982, the inmate population reached approximately 5,500 an increase of almost 2,500 inmates in four years, with nearly half of the increase occurring in one year. Coinciding with this explosion, Arizona experienced its largest and most sustained reduction in reported crimes in over two decades.

In 1982, policy makers increased sanctions for those offenders who committed new crimes while on supervised release such as probation or parole. House Bill 2004 modified the Arizona Revised Statutes, Section 13-604, by adding Section 13-604.01. The new section mandated a "must serve" provision for those

convicted of a non-dangerous offense and further mandating a term of imprisonment not less than the presumptive sentence for that offense class. This new sentence would also have to be served consecutively with any other sentence or sentences the offender was serving at the time of the conviction.

For those convicted of a dangerous offense, one involving the use of a deadly weapon or inflicting serious physical injury, the term of imprisonment was set at life with no possible release until twenty-five years had been served. This sentence would also be served consecutively with any other sentence. Prison population and reported crimes continued on the same trends begun in 1981 as the legislation became law.

Shortly after House Bill 2004 passed in 1982, a Department of Corrections' staff analysis stated that this bill alone could, if interpreted literally by prosecutors and courts, produce a much more profound impact on prison population than the 1978 criminal code revision. Also, given the mandatory twenty-five year minimum terms for dangerous offenses, the full impact would not be felt until early in the twenty-first century.

The predicted impact from this bill has not been realized due in part to problems with the prediction model, but more importantly because of system response to the provisions of the bill. A follow-up analysis conducted in 1984 found that only about ten percent of offenders eligible for the dangerousness provision of Section 13-604.01 had actually been sentenced under the Section. The other ninety percent, although convicted of crimes such as aggravated assault and armed robbery which were included in the intent of the legislation, were sentenced as non-dangerous offenders and received sentences substantially less than the twenty-five calendar years.

While other states have enacted similar legislation, a recent study (Bureau of Statistics and Policy Research, 1986) of Pennsylvania's 1982 mandatory sentencing law offered some evidence that the adjudication process does indeed adapt to new laws in ways which may not be wholly in keeping with the spirit and intent of the changes. This study presented evidence that both conviction rates and sentence lengths fell below expectations following enactment of the 1982 law in Pennsylvania.

Passage of House Bill 2004 in Arizona was considered a major weapon in the battle to incapacitate repetitive or dangerous criminals. It allowed for substantial increases in the level of sanctions available to prosecutors and courts. Due to provisions set forth in the 1978 Criminal Code, however, prosecuting attorneys must allege and prove in court the defendant's prior conviction record as well as conditions of dangerousness necessary to pursue the mandatory life sentence.

RESEARCH OBJECTIVES

In practice, the above necessities are often difficult to develop given relatively short time frames and increasing caseloads. The primary objective of this research is to determine how prosecutors and courts adapted to the requirements of House Bill 2004 and whether these actions resulted in keeping with the spirit of the law and with the intent of the law to deter and incapacitate criminals.

One method of dealing with the spirit of the law is for the system to adapt to the new requirements in a manner that will serve two purposes: insure a conviction and subsequent prison sentence to immobilize the offender and prevent the commission of new crimes in the immediate future; and to establish provisions for repetitiveness within a context that would allow, for future use, easier allegation and proof.

Plea bargaining is one widely used tool for serving these purposes. By offering to drop the allegation of repetitiveness or dangerousness in exchange for a

plea of guilty, a prosecutor can virtually assure a defendant a shorter sentence and preclude the possibility that a weak case would result in acquittal.

OBTS-type data bases contain a wealth of information regarding original charges and any changes that occur during adjudication. By tracking cases through this process, the points at which charges are modified can be identified and analyzed. Primary topics of interest would include:

1) How often, and at what points, are charges or "aggravating" factors modified?

2) Who is most likely to enter into a plea agreement?

3) Are plea agreements as prevalent as they appear to be?

4) Do defendants who hire private counsel enter into plea agreements more or less frequently that those who use public defenders, and do sentencing disparities occur under the two types of counsel?

5) Are defendants who are subject to the provisions of A.R.S. 13-604.01 more or less likely to enter into a plea agreement than other criminal defendants?

6) Do repetitive or dangerous offenders who enter into plea agreements receive significantly longer or shorter sentences than those who opt for a trial?

In order to assess the degree to which the adjudication process adapted to the requirements of A.R.S. 13-604.01, these same questions can be applied to cases which began before the effective date of the policy. Another issue which this research will address is:

7) If the system did change to improve case processing efficiency and speed at the sake of following the letter of the law, was this change gradual or abrupt?

Gradual change in the process could likely imply an evolutionary growth, or a development to meet changing demands for resources, which leads to a final issue:

8) Were the resources available to prosecutors and courts (e.g., budgets and staff) sufficient to meet the changing demands? Did the demand increase so rapidly that these components were unable to foresee the change and to plan for it?

REVIEW OF THE LITERATURE

The Uniform Crime Report (UCR) has historically served as the "official" crime statistic. As a measure of *actual* crime levels, though, UCR data by definition are biased.

This bias may be due to underreporting by citizens (e.g., Zedlewski, 1983); to changes in organizational objectives or composition (McCleary et al., 1982; Boland and Brady, 1985); to increased social complexity (e.g., Green and Allen, 1982); or to unequal enforcement of laws (Blumstein and Cohen, 1973; Bohm, 1986; others). In

other words, UCRs are the outcome of an often unknown, and sometimes unmeasurable, generating process.

In a comparison of UCR versus National Crime Survey (NCS) data, Zedlewski (1983) found UCR based estimates of victimization risk on police services were consistently significant for burglary and property offenses, while estimates based on NCS data were never significant. This finding was explained as "...changes in police manpower are bureaucratically determined..." (p. 272) and that "...police statistics are influential in determining police resources even if they don't reflect underlying risks." (p. 273)

McCleary et al. (1982) used three time-series quasi-experiments to show how organizational changes affect UCRs. In the first, the level of UCR burglaries dropped immediately and dramatically after detectives were required to investigate burglary complaints. The second demonstrated how discretionary behavior of police officers is rewarded when that behavior produces the outcomes desired by the chief. In the third, UCR coding was done literally, with a corresponding change in UCR level, after uniformed officers--and their discretionary judgments--were removed from supervisory positions.

As society grows more complex, the system of values changes (e.g., Durkheim, 1893). One result of this is that more behaviors are codified into legal norms (Dye, 1966). Although social complexity may produce a more diffuse set of norms, increased social complexity may also lead to a higher incidence of deviant behavior and public pressure for more severe punishments (Green and Allen, 1982). There are also indications that it may be a growing rate of *certain* crimes, rather than *all* crimes, triggering public concern.

Unequal enforcement of existing laws may be due to a number of factors related to the types of offenses (Bohm, 1986); to low visibility and enhanced discretion of police agencies (Hagan and Zatz, 1985); to differential treatment of suspected criminals (Petersilia, 1985; Sigler and Horn, 1979); or to organizational behavior patterns and resources (Blumstein and Cohen, 1973; Votey and Phillips, 1972).

Imprisonment rates represent the extreme societal response to crime, and are related to UCRs in an indirect fashion; UCRs often represent the beginning of the process leading to imprisonment. As with UCRs, imprisonment statistics represent the outcome of certain generating processes. Unlike UCR statistics, however, these generating forces are much more accessible to researchers and, over the past three decades, a wealth of literature has been produced to describe these processes.

Court processing literature has explored the effects of reducing or increasing discretion at various points in the process (Crozier, 1964; Baum, 1984; Nagel and Geraci, 1983); focused on differences in processing and sentencing (Farrell and Swigert, 1978; Hagan and Zatz, 1985); and argued over the effects of caseload pressures (Votey and Phillips, 1972; Geerken and Gove, 1977; Heumann, 1975; Nardulli, 1979). More importantly, this research has addressed the relationships among decisions made at various point in the process (Clarke and Kurtz, 1983; Eisenstein and Jacob, 1977; others) and how those decisions affect outcomes, especially perceived sentencing differentials due to plea bargaining (Brereton and Casper, 1981; Church, 1976; Newman, 1956).

The impact of crime control legislation cannot, and should not, be attributed solely to the legislation. Instead, impact studies must place the results within the context of the process generating the observed outcomes, especially in regards to how the policy is implemented. Recent studies on new sentencing legislation in Pennsylvania (1986) and Colorado (1987) have produced conflicting evidence of compliance based on sentencing outcomes. The Colorado study also surveyed felony court judges across the state to determine their perception of the policy's

provisions, and offered tantalizing evidence that outcomes (sentences) met the letter of the law because the statute agreed with the judges' perception of proper sentencing ranges.

This phenomenon is well documented (see Baum, 1984, 1981) and can be viewed as one of the crucial issues in successful policy implementation, and is further supported by research on plea bargains. For example, Eisenstein and Jacob (1977) found that the mode of disposition (plea vs. trial) accounted for very little of the variance in sentence length, and Rhodes (1979) reported that judges did not "reward" guilty pleas with more lenient sentences. Moreover, Nardulli et al. (1985) offer a model of processing based on "consensus" where the key actors share a common sense of "just" punishment. This concept is an extension of an earlier work (Mather, 1973) which offers "shared expectations" of prosecutors and judges as one mechanism which works to dispose of cases via pleas.

At the heart of all crime control policies is the desire to prevent future offenses--deterrence--and to punish offenders for their actions--retribution and deserts. As Davis (1985) notes, though, deterrence is not itself an aim likely to lead to a theory of *just* punishment. Just deserts principles do not allow more punishment than what is *deserved*, while many of the recently introduced statutes set punishments far greater than that (see also Von Hirsch, 1985). Baum (1984) has stated that the attitudes of implementors (judges) are shaped by their "policy preference" or what they perceive to be good policy. In turn, attitudes are a central force in determining behavior and, thus, the manner in which the policy is implemented (Thompson, 1984).

From this perspective, disparities between legislative intent and policy implementation become more understandable. The Colorado study (1987) found that the new statutes matched the judges' policy preference and there was no difference between intent and implementation; in other cases (e.g., Pennsylvania) such congruence was not present. In situations where the policy and judges' policy preference disagree, adaptive measures (e.g., Heumann and Loftin, 1979; Church, 1976) ensure that organizational goals are met while optimizing the flow of cases (Votey and Phillips, 1972).

It is not always possible to collect data related to judges' policy preferences when assessing the impact of new legislation, especially when some time has elapsed since the legislation was enacted. By assessing differences in process and outcome variables before and after enactment, it is possible to make inferences regarding possible changes in behavior.

In 1982, California voters approved Proposition 8, which added Section 1192.7 to the state penal code. Termed the "Victim's Bill of Rights," Proposition 8 was designed to end plea bargaining for a number of serious crimes such as murder and rape. The precise wording of the proposition restricted the behavior of superior (felony) courts, but not of municipal (lower) courts. During the first two years of experience, the proportion of cases disposed of by trial in superior courts *decreased* (McCoy and Tillman, 1985), which was attributed to a shift of plea bargains from superior to lower courts.

Even earlier, in 1969, California amended Section 17 of the state penal code to allow adjudication of lesser felonies in municipal court at the discretion of the prosecutor. Meeker and Pontell (1985) noted that the rate of "slow pleas," or those entered late in the process, increased after enactment. They also remarked that when sweeping policy changes are introduced, the nature of the courts assures that these changes produce a chain reaction of adjustments that may not have been anticipated.

What this research seems to indicate, then, is a rift between what legislators and courts perceive as effective crime control policy. This is exemplified by a judge's comment:

"The Legislature thinks that the answer to all crime is to simply increase the punishment. Punishment is not going to solve the problem..." (Mather, 1973; p. 194)

Although this comment was directed at a specific offense, it reflects the deeper schism often observed between legislative intent and implementation, a schism magnified by legislators' lack of experience with criminal processing and judges' immersion in that process. In other words, the policy makers are typically only aware of gross circumstances, while the policy implementors deal daily with specific details.

As the importance of research on crime control legislation and criminal processing has increased, so has the sophistication of the methods and models used to assess the effectiveness of legislation and processing decisions. In this study, we develop time-series ARIMA models and probit regression models that make use of existing OBTS-type data to study the implementation of strict policy dealing with repetitive offenders who commit new crimes while on supervised release.[1]

This statute was enacted in 1982 and provides severe penalties for offenders convicted of a new offense. Primarily a reactionary, retributive policy, it is of concern for a number of reasons:

1) it was directed at a specific population of repetitive offenders, those who were under supervised community release at the time the new offense was committed;

2) it provided for severe and, in some cases, specific sanctions against those convicted of a new offense; and

3) it seemingly removes considerable discretion from the courts regarding imposition of sentences.

Time-series (ARIMA) models have been used extensively in legal impact assessments over the past two decades. They have been used to determine the effects of enforcing speeding laws (Campbell and Ross, 1968; Glass, 1968); the effect of stringent gun control legislation (Deutsch and Alt, 1977; Hay and McCleary, 1979); the relationship between crime rates and police expenditures (Land and Felson, 1976); and have been applied extensively to the enforcement and effectiveness of drunk-driving legislation (Ross et al., 1970; Epperlein, 1987).

These models provide advantages over other approaches to impact assessment in that they can help determine the structure of the impact as well as producing accurate and concise estimates of the degree of change.[2] ARIMA impact assessment models also require a fairly long series of postintervention observations, though, and require special computer software for optimizing parameter estimates.

Probit models are appropriate when the behavior being measured is qualitative behavior as in the dichotomous case of whether an offender plea bargains or not. The model which results is known as the linear probability model, and its coefficients are interpreted as probabilities of an event occurring.

DATA, ANALYSES, AND RESULTS

The data used in the study were provided by the Law Enforcement-Justice Information System (LE-JIS) for Maricopa County, the most populous county in Arizona. They consist of case processing histories for all felony offenders from 1979

through 1987, from the starting date of the court process in the justice courts through the disposition date in the superior court. Information is also included on the offenders sex, race, age, type of attorney used, type of charge, number of counts, perceived dangerousness of the offender, whether the offender was on probation, type of sentence (probation or prison), and length of sentence. Due to the size of the population (61,000+ cases), and the computational costs involved in analyzing it, a sample of 2,583 cases (males only) was selected to represent the population. A variety of statistical methods were employed to analyze the data, including frequencies, descriptive statistics, probit regression analysis, and time-series analysis. We follow with results of these analyses and the research questions they address.

How often and at what point are charges changed?

Changes from original to disposition charges, number of counts, felony to misdemeanor status, and dangerous to non-dangerous status occurred in 58.1 percent of the 2,583 sample cases processed through superior court. In 41.9 percent of the cases, there was no change in any aspects of the charge.

In Table 1, the Target group denotes those on probation with new offenses and thereby affected by the new law. For the Target group, the prevalence of *any* change from case filing to disposition increased by 9.2 percent; for the Other group (i.e., those not on probation), changes decreased by 8.4 percent. During a period when the majority of cases, those not under probation supervision at filing, were less likely to experience some type of reduction, the group targeted by A.R.S. 13-604.01 became more likely to have at least one component of their case reduced.

Table 1. Changes in Charges Before and After 1982 Crime Control Law

		Percent of Cases Changed		
		Before	After	Change
Number of Counts	- Target	26.4%	43.5%	+64.7%
	- Other	26.5%	35.6%	+34.3%
Offense Charged	- Target	11.5%	18.1%	+57.4%
	- Other	31.5%	30.2%	-4.1%
Felony Reduced to Misdemeanor	- Target	12.6%	10.9%	-13.5%
	- Other	26.9%	15.4%	-42.8%
Dangerous Reduced to Non-Dangerous	- Target	2.3%	6.4%	+178.3%
	- Other	3.6%	5.7%	+58.3%
Any Change	- Target	42.5%	46.4%	+9.2%
	- Other	62.8%	57.5%	-8.4%

What are the demographic characteristics of those who plea bargain?

Probit regression analyses were conducted to determine the characteristics of those individuals who were likely to plea bargain. Independent variables consisted of race, type of defense attorney, age, probation status, dangerousness status, and type of criminal charge (crime against person, property, drug or other). Table 2 provides coefficients, standard errors, t-ratios, and probabilities from these analyses. Offenders most likely to plea bargain were those charged with dangerous crimes.

Those offenders who were not on probation were most likely to be offered plea bargains.

Table 2. Probit Regression Coefficients for those who Plea Bargain

Variable	Coefficient	Std. Error	T-Ratio	Probability
CONSTANT	0.26497	0.14255	1.85880	0.06307
Race	-0.00136	0.02077	-0.06570	0.94760
Public Attorney	-0.04637	0.04117	-1.12644	0.25996
Age	-0.00389	0.00319	-1.21878	0.22291
Probation	-0.42342	0.09611	-4.40559	0.00001
Dangerousness	0.89302	0.13014	6.86208	0.00000
Original Charge	0.02575	0.04071	0.63245	0.52711

Log of likelihood function = -1461.7640026
Chi-square statistic for significance of equation = 79.02077
Degrees of freedom for chi-square statistic = 6
Significance level for chi-square statistic = 0.0000

What changes occurred in patterns of demographic characteristics after the 1982 legislation?

Before the law was enacted, offenders on probation were less likely to plea bargain than those who were not on probation ($t=-3.43$, $p=.001$). This is probably due more to their not being offered the opportunity to plea than their refusing it. Defendants charged with dangerous offenses were more likely to plea bargain ($t=2.77$, $p=.006$).

After the law was enacted, similar patterns prevailed with probationers less likely to plea bargain ($t=-2.96$, $p=.003$) and those whose original charge was considered dangerous more likely to plea bargain ($t=6.38$, $p=.000$). Thus, the law had no effect whatsoever on the likelihood of who would be plea bargaining.

Do public or private attorneys plea bargain more often?

Contingency table analysis of attorney type and plea bargaining indicates that there is a significant difference between private and public attorneys. Private attorneys tend to plea bargain more often. However, the relationship between the two variables, while significant (chi-square=6.8, $p=.033$), is very weak (Cramer's $V=.051$).

Those weak but significant differences are attributed to type of attorney and plea bargaining before the law (chi-square=10.78, $p=.005$), but after the law is enacted, differences are no longer significant.

When examining the type of plea bargain taking place--whether on charges, felony reduction, or dangerousness status--the following changes were observed before and after the law:

Table 3. Differences in Types of Pleas

Type of Plea Bargain	Chi-Square	Prob.	Cramer's V
Reduction in Charge			
- Before	4.19	p=0.007	0.07
- After	6.61	p=0.037	0.06
Felony Reduced to Misdemeanor			
- Before	9.83	p=0.007	0.12
- After	5.40	p=0.067	0.05
Dangerous Reduced to Non-Dangerous			
- Before	0.35	p=0.839	0.02
- After	0.83	p=0.660	0.02

Type of attorney, therefore, had impacts on charge and felony bargaining but made no difference in whether a dangerous charge was bargained. All relationships were weak, though.

Are there differences in sentences between clients of public and clients of private attorneys?

Contingency table analysis indicates that public defenders are significantly (chi-square=22.74, $p<.001$) more likely to receive prison sentences for their clients than are private attorneys. As is expected, therefore, they are also less likely to receive probation sentences (chi-square=23.93, $p<.001$). Both relationships, while significant, are relatively weak (Cramer's V=.09 and .10, respectively).

Clients of public attorneys are also more likely to receive longer prison sentences (chi-square=44.67, $p<.001$) and shorter probation sentences (chi-square=74.95, $p<.001$). Such information could be important for planning of resources for both probation and prison departments since the majority of offenders are being represented by public attorneys. Changes in the mix of public and private defense attorneys could indicate resultant resource demands on probation and prison resources. This is certainly an area for further research.

The outcome pattern of more prison sentences for clients of public defenders and less probation sentences held true both before and after the 1982 legislation. Similarly, sentence length patterns were somewhat consistent before and after the law except that before the law there were no significant differences between public and private attorneys in the length of prison sentences their clients received.

Do offenders on supervised release plea bargain more often?

The findings are consistent and significant (again, however, with weak associations) in this area--those on probation supervision status are not plea bargaining. It is not known whether they are being offered the opportunity to plea bargain and refusing it, or are not being offered the opportunity at all. The latter scenario seems more likely. The only deviation from this pattern is in plea bargains that reduce the dangerousness status. There is no significant difference between being on probation supervision status or likelihood of having a dangerousness plea, just as there were no significant differences between the type of attorney and dangerousness pleas.

Patterns are similar after the law except that there is a reduction to nonsignificance for those who plea from a felony to a misdemeanor. In other words,

after the law was enacted, those on probation supervision status are no more likely to plea down to a misdemeanor than those not on probation supervision.

Are sentences for "repetitive and dangerous" offenders longer for those who plea bargain or for those who go through the entire court process?

There were too few cases of repetitive and dangerous offenders to be able to differentiate their court processing. However, the entire sample of 2,583 cases was examined for differences in sentence outcomes and lengths. The results showed that probation sentence lengths were significantly shorter before the new law (chi-square=43.30, $p<.001$) and prison sentence lengths were longer after the law (chi-square=73.78, $p<.001$). As far as outcomes are concerned, an offender was more likely to go to prison after the law (chi-square=36.64, $p<.001$). There were no significant differences in whether a person received a probation sentence before or after the law.

What processing changes took place after the law? Were they abrupt or gradual?

In this section, the focus of the analysis is shifted from case processing to aggregate statistics. For individual cases, the analysis provided useful information on the types of offenders and their characteristics as well as differential processing rates among various offender types. For the aggregate data, the analysis will focus on changes in processing these offenders as *groups*. This will allow a further understanding of how factors external to the court system, such as changes in laws, can affect the process outputs.

Figure 1 shows the entire population of felony case dispositions by month, from January, 1979 through August, 1987, separated by those defendants that came into the court process while on probation (i.e., those affected by A.R.S 13-604.01) and those defendants that were not on probation (i.e., those generally *not* affected by A.R.S. 13-604.01).[3]

The non-probation dispositions show an erratic pattern immediately before and after the intervention point, and a steadily increasing pattern beginning in the second year following the intervention. There does not seem to be any systematic change immediately following the intervention, however--a fact which is supported by the statistical analysis.

Case dispositions for defendants on probation show the same general pattern as the non-probation cases. Dispositions are erratic just before and after the intervention, and begin to move upward approximately two years following the intervention. Again, statistical analysis supports the tentative conclusions from examining the graph; enactment of A.R.S. 13-604.01 did not impact the number of felony case dispositions.

Case processing time refers to the number of days from case filing to disposition. The data shown in Figures 2a and 2b represent the mean processing time, by month, for non-probation and probation cases disposed of from January, 1979 through October, 1987.

For non-probation cases (Figure 2a) the mean processing time appears to stabilize following enactment of A.R.S. 13-604.01. The series level, though, remained constant after the intervention with some indication of a slight drift upward. The graph indicates no impact and this conclusion is upheld by the statistical analysis.

The processing time series for probation cases (Figure 2b) presents a more interesting picture. Although there is no indication of a change in series level following enactment of A.R.S. 13-604.01, the series *variance*, or the difference between successive observations, appears to increase dramatically during the last

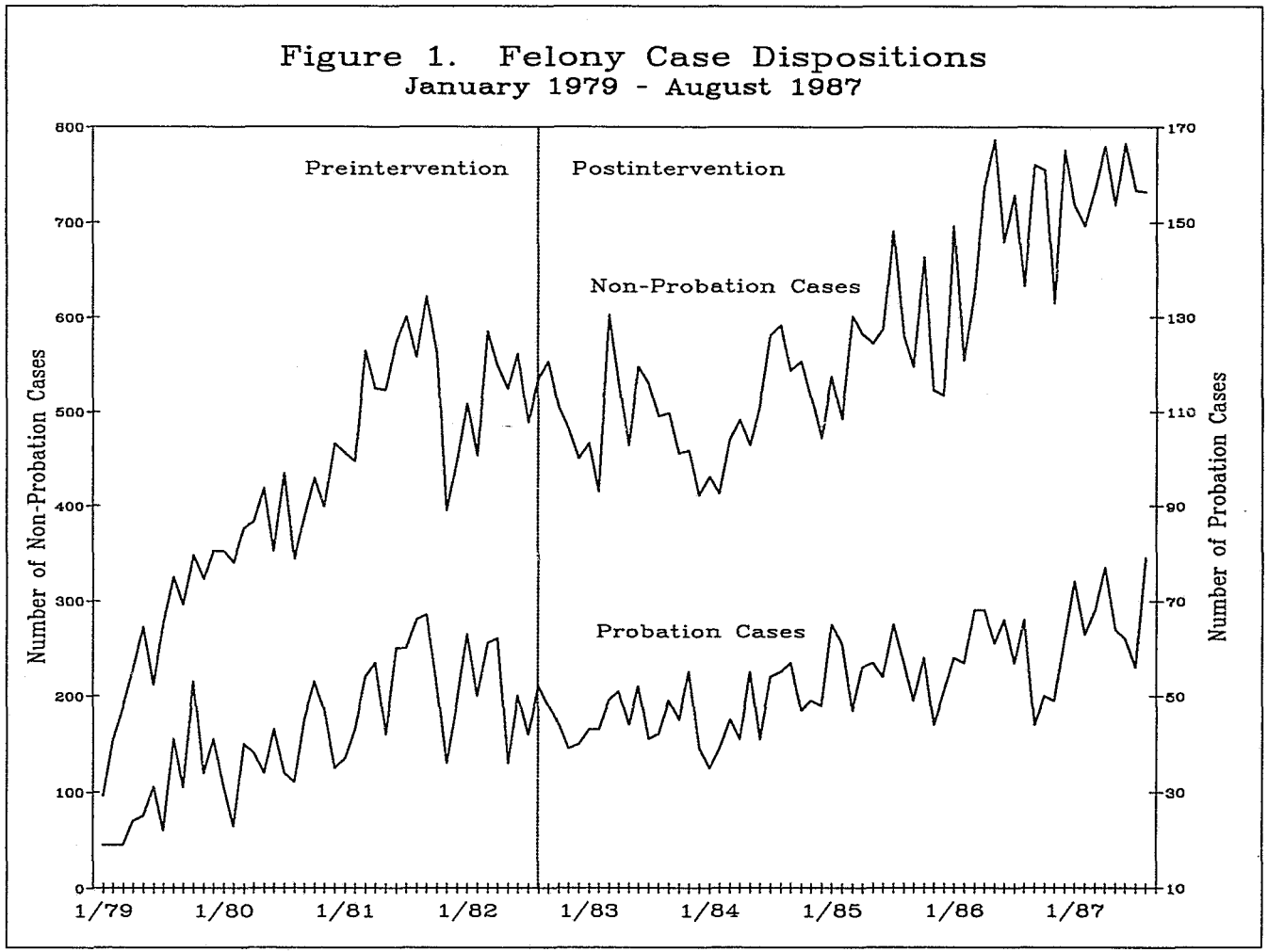


Figure 1. Felony Case Dispositions
January 1979 - August 1987
Preintervention
Postintervention
Non-Probation Cases
Probation Cases
Number of Non-Probation Cases
Number of Probation Cases
800
700
600
500
400
300
200
100
0
170
150
130
110
90
70
50
30
10
1/79
1/80
1/81
1/82
1/83
1/84
1/85
1/86
1/87

Figure 2a. Case Processing Time in Non-Probation Cases
January 1979 - October 1987

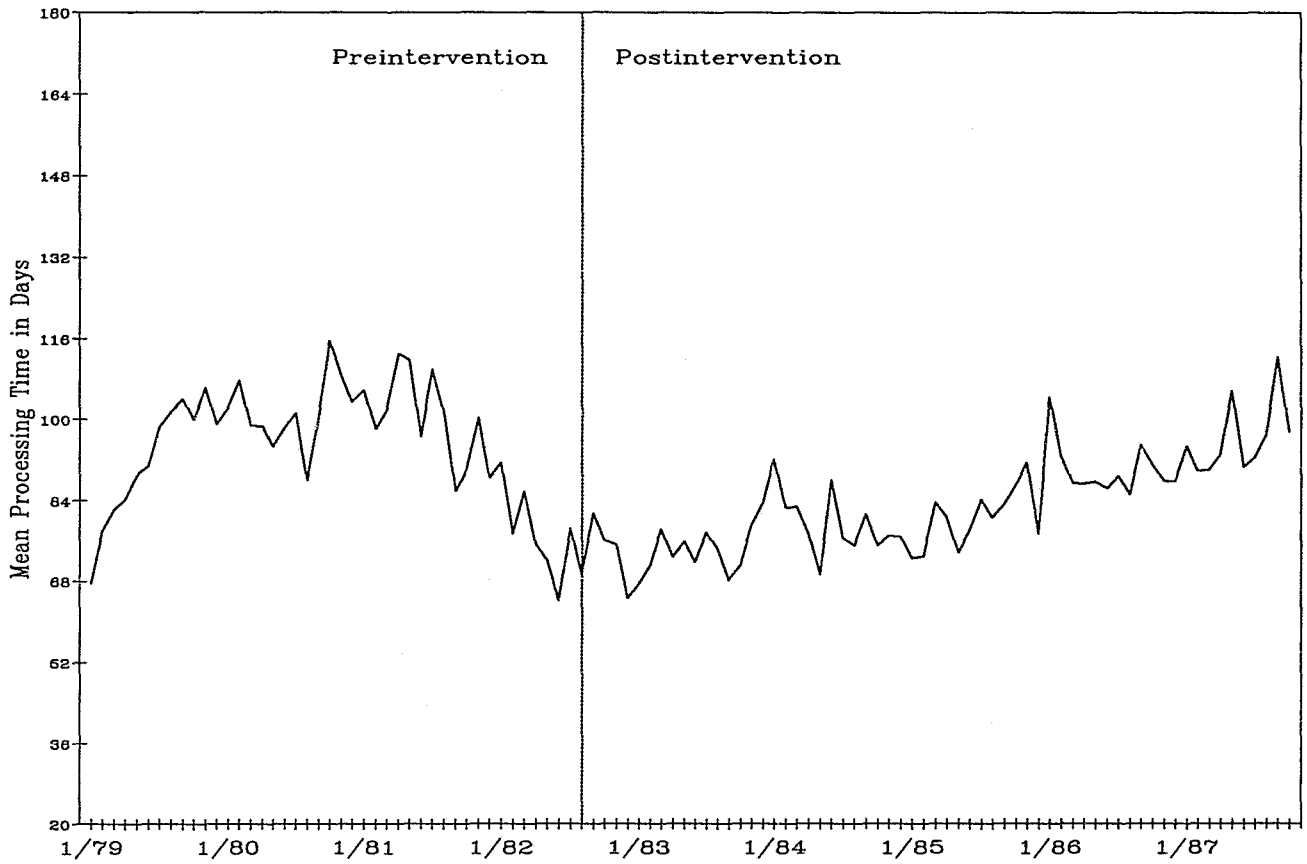
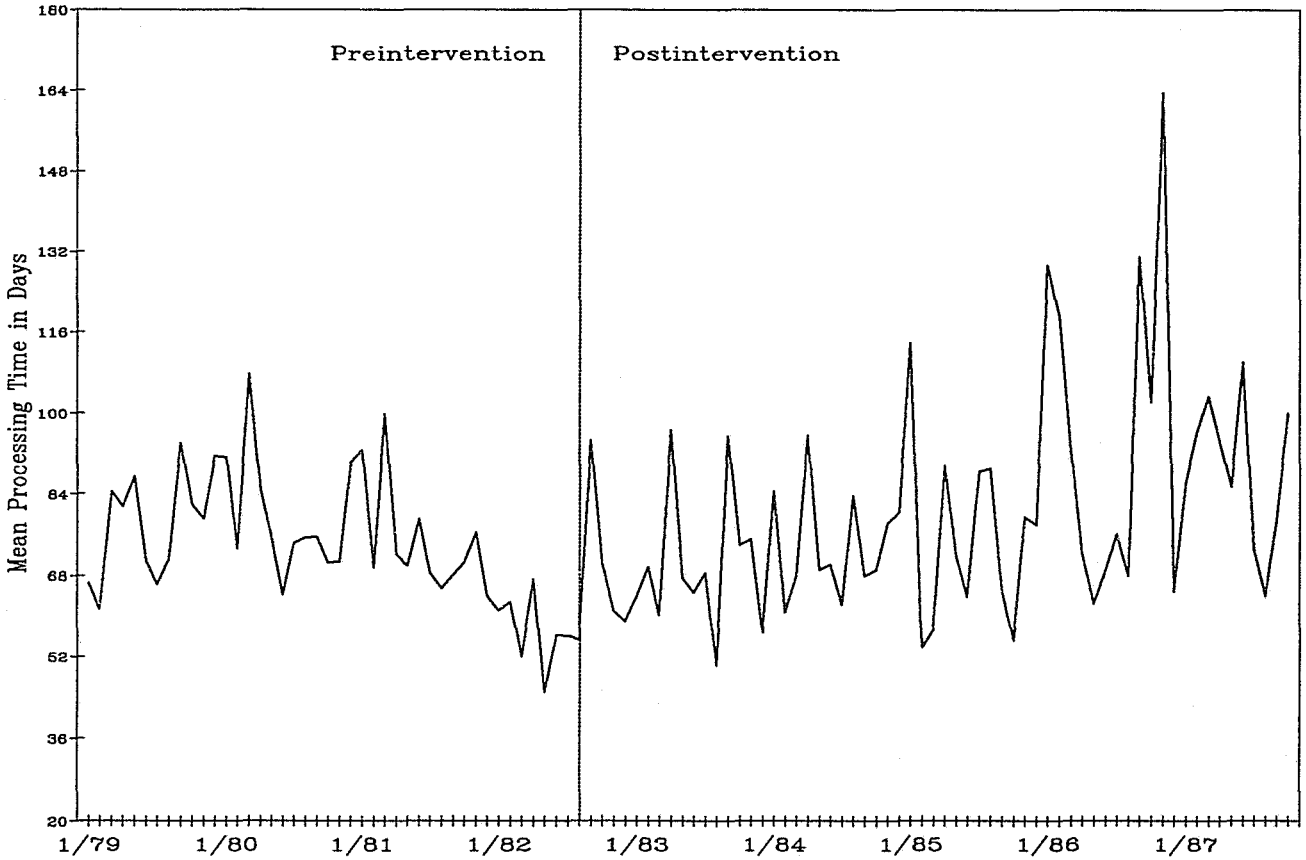


Figure 2b. Case Processing Time in Probation Cases
January 1979 - October 1987



two or three years of observations. Even though the intervention had no impact on the series level, there does seem to be some effect on the series variance. Given the relatively small number of cases in this group, approximately 60 per month, a few extreme values could easily produce the observed effect.

Arizona's 1978 criminal code revisions organized offenses into a structure of *felony classes* ranging from the most severe (Class 1) to the least severe (Class 6), with sentence length corresponding to the felony class. Misdemeanors were also categorized in this fashion, except that only three classes were established--though this analysis focuses strictly on cases filed as felonies.

One method of complying with the letter of the statute, but not the spirit, would be to reduce the felony class charged to the offense; in effect, reducing the severity of the offense. By reducing only the felony class, the defendant could still be convicted of the same type of crime (e.g., assault or burglary) but would be subject to a shorter sentence.

As presented in Figure 3a, the proportion of felony class reductions (non-probation cases) grew steadily over the length of the series; the intervention produced no distinguishable visual impact. In Figure 3b, how ver, the proportion of felony class reductions for probation cases shifts rapidly following the intervention, a shift which seems to be permanent. For both series, statistical analysis once again supports the conclusions reached through visual inspection of the graphs.

For the first through the forty-fourth month (i.e., January, 1979 through August, 1982) of the probation series, prosecutors and courts agreed to reduce the felony class in 15.9 percent of the cases processed. Such reductions could occur as the result of an improper charge by the police; such an instance would be rare, however. The county attorney is responsible for filing the case with the courts and should verify the offense charged, the proper felony class, and other facts regarding the offense.

Beginning in September, 1982, felony class reductions rose rapidly and, except for a very few months, the proportion remained at or above the previous high months. This pattern has continued since enactment of A.R.S. 13-604.01 and has resulted in an increase of fifteen percentage points over the preintervention level.

Another available option for reducing the probability that an offender would spend a long time in prison is to reduce a felony offense to a misdemeanor. While this option would most likely not be used often, and very rarely in the higher felony classes, it might be a viable alternative for lower (Class 5 or Class 6) felonies.

Judges apparently are not exercising this option. As shown in Figure 4a, felony to misdemeanor reductions for non-probation cases dropped rapidly from 1979 through 1982. The postintervention series, from late 1982 onward, displays a less pronounced decline but no real impact.

For probation cases (Figure 4b) the preintervention series varies wildly about a constant level. Immediately following enactment of A.R.S. 13-604.01, though, the series seems to reach a new, higher level albeit temporarily. Within two years after the intervention, the series variance appears to stabilize while the series level seems to decline from mid 1984 through 1987. The statistical models for these two series indicate no impact.

CONCLUSIONS

The enactment of A.R.S. 13-604.01 was heralded as a means to punish dangerous and repetitive offenders by requiring mandatory, consecutive sentences for those convicted of a new crime while on supervised release. This law also mandated that those offenders on supervised release who were convicted of a new, dangerous offense would serve a flat twenty-five calendar years prior to release.

Figure 3a. Felony Class Reductions in Non-Probation Cases
From Case Filing to Disposition
January 1979 - October 1987

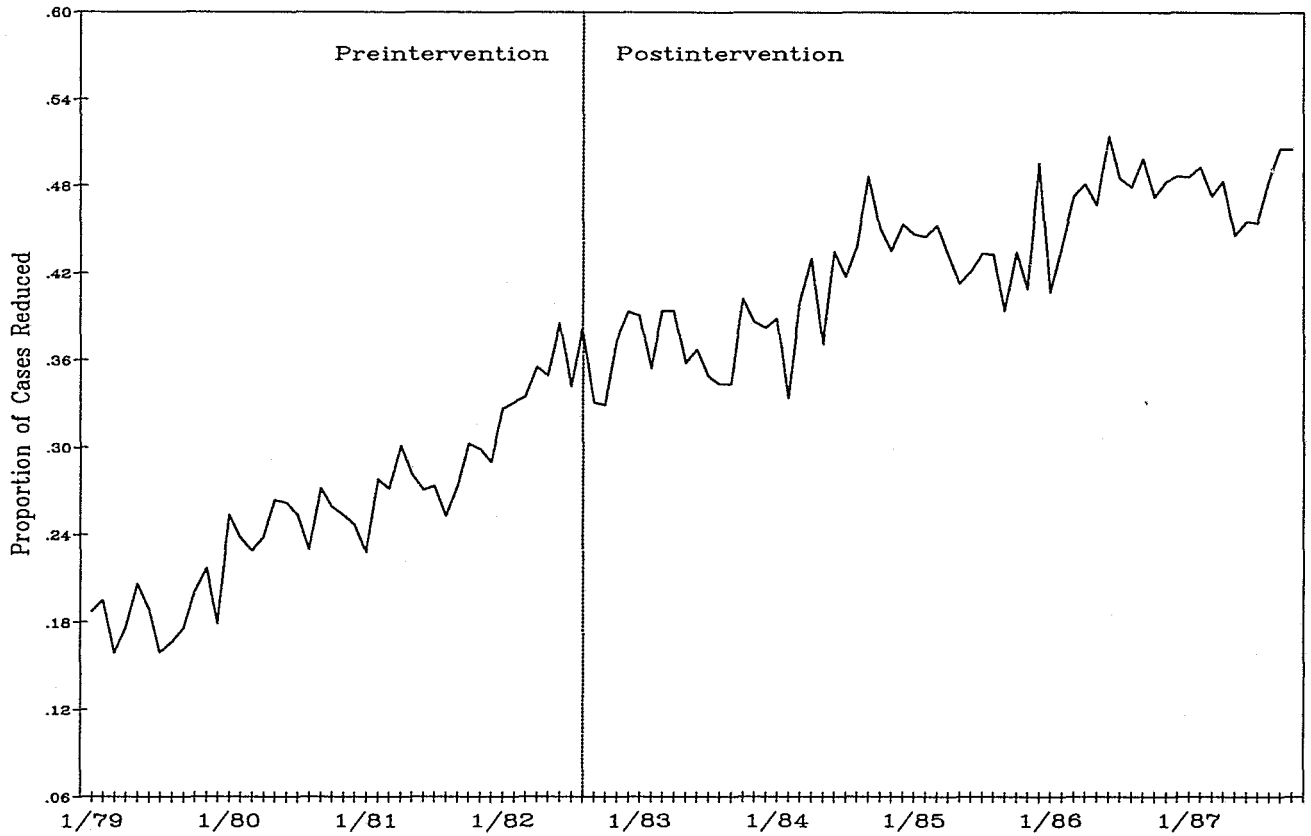


Figure 3b. Felony Class Reductions in Probation Cases
From Case Filing to Disposition
January 1979 - October 1987

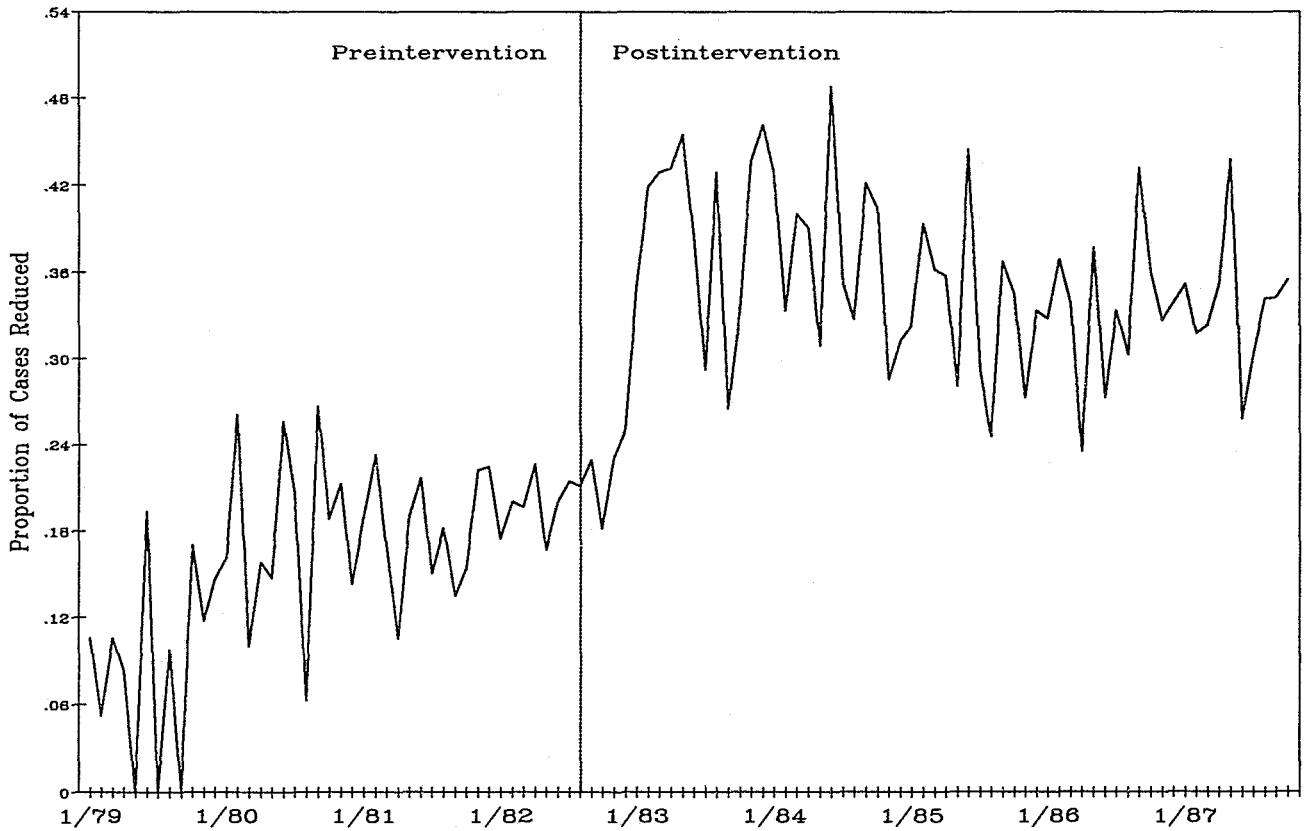


Figure 4a. Felony to Misdemeanor Reductions in Non-Probation Cases, From Case Filing to Disposition January 1979 - October 1987

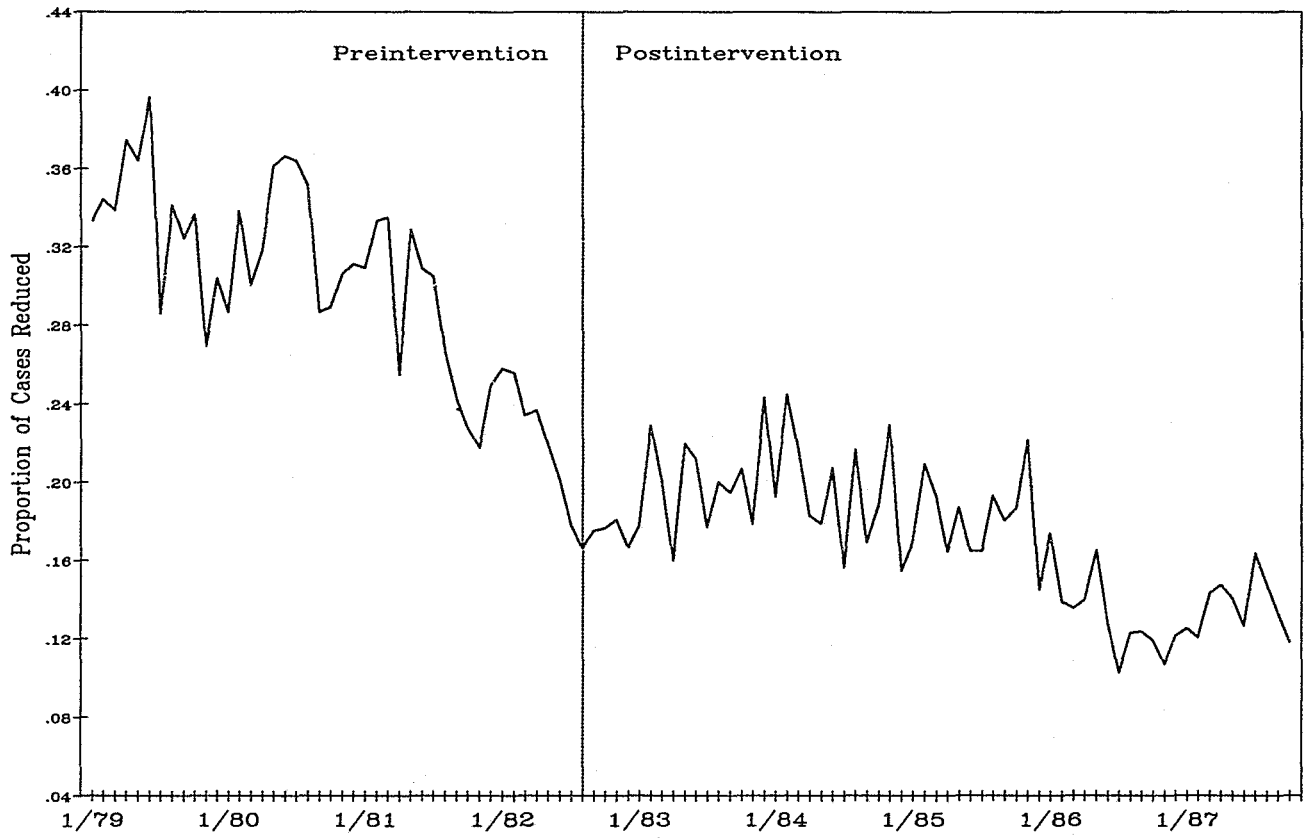
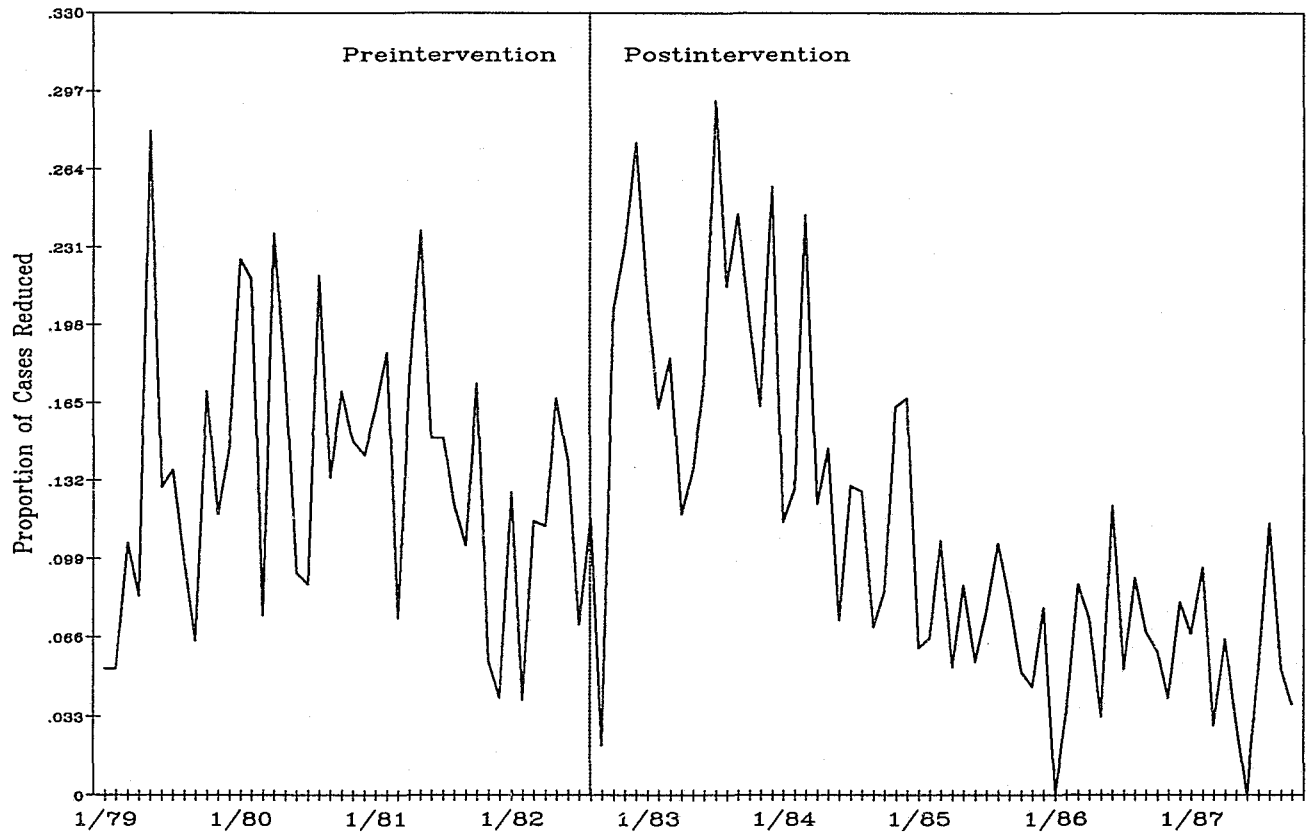


Figure 4b. Felony to Misdemeanor Reductions in Probation Cases, From Case Filing to Disposition January 1979 - October 1987



Successful implementation of public policies seems to depend on the presence of many important factors: the degree of public concern about the need for the policy and the ability of policy makers to accurately gauge that concern; the degree of specificity regarding objectives, duties, and priorities given by the policy statement; sufficient resources to carry out the intent of the policy; and a convergence of attitudes and interests between the policy makers and the policy implementors (see Thompson, 1984; Baum, 1984; Edwards, 1980; Nakamura and Smallwood, 1980).

Additionally, crime control policies are subject to often conflicting theoretical and philosophical foundations of deterrence, retribution, incapacitation, and just deserts. Deterrent policies should have a structure of penalties that is designed to discourage as much law-breaking behavior as is possible, while just deserts principles structures the punishment more to the circumstances of the offense and the offender (Davis, 1985). Both positions, however, are dependent upon a "tariff" or "going rate" concept of punishment.

This research found that the incidence of plea bargaining for those offenders who were on probation increased following enactment of A.R.S. 13-604.01 . Most notably, the incidence of plea bargaining by those charged with dangerous offenses increased by 178.3 percent. Given the provisions of the new statute, these offenders arguably stood to lose the most--in loss of liberty--of all those affected by the statute. Moreover, the Arizona Criminal Code structure could produce a sentence differential of over twenty-three years between a conviction for a dangerous offense and a conviction for a non-dangerous offense. Such a differential might serve the aims of retribution and deterrence, but not those of just deserts. Plea bargaining can serve a useful purpose in reconciling such differences, and this study found strong evidence that the pattern of pleas changed after implementation of the new law.

What has happened, however, is that although there is more pleaing to lower charges since the law's inception, the prison sentences given for those lower charges have been longer. It appears therefore that all offenders, both dangerous and non-dangerous, are being given longer sentences--though not as long as the law prescribes. Judges are retaining discretion to a larger extent than originally thought. While discretion shifted to prosecutors in terms of the types of charges and plea bargains conducted, judges nevertheless retained control over the length of sentences, and those prison-bound offenders are probably assessed by the judges' value of dangerousness. This tends to preserve the "going rate" (Loftin et al., 1983) as more research is discovering. Laws consequently are used as much as symbolic statements (Nienstedt, 1986) as they are as policy statements. This is decidedly true in Arizona's experience with A.R.S. 13-604.01's implementation, a law which was passed in reaction to a particularly heinous crime involving an offender on work release who kidnapped and murdered a young woman.

The bulk of prior research on plea bargaining tends to focus on how the agreement serves the needs of either the prosecution or of the defense. While this is a natural dichotomy and easy to conceptualize, it would seem reasonable to direct future research toward explaining plea agreements in terms of available resources and whether or not the values of the actors, such as prosecutors and judges, are similar (e.g., see Green and Allen, 1982; Mather, 1973; Nardulli, et al., 1985; Von Hirsch, 1985).

There were some limitations to this research which should be noted. The data were limited to examining those offenders on the supervised release status of probation. Therefore offenders on parole were not included in the study. Further, the task of "cleaning" the data and file management took more time and resources than were budgeted or expected. Although we had the entire population of offenders who went to superior court, we were not able to use them. (Comparisons

of percentage breakdowns from the population to the sample revealed little difference, however.)

There was also an inability due to these constraints to properly prepare files for a proposed event-history analysis. We decided instead to approach the research question from a perspective that is somewhat new to applied researchers but is readily understood with a basic understanding of regression analysis. For further reading on probit regression models, we especially recommend Schmidt and Witte (1984).

Future research should continue along the lines of using new methodologies to answer questions being asked about the effects of more punitive laws and policies towards offenders. Processes, especially, should be examined in depth because although laws are passed, they are not always implemented as intended. The question remains then as to the intent of the legislative branch in passing such laws. Are they symbolic or are they meant to be implemented as written?

Data requirements of the new methodologies are sometimes extensive. Government entities are already collecting massive amounts of data but are not utilizing these data in research to any great extent. Moreover, there are problems with incomplete entries, reporting changes, lack of verification, etc. Many offender-based tracking systems have weak links between agencies and, in some cases, there are no links at all because of a lack of uniformity. For example, in the LE-JIS data base, arrest date which is entered by the sheriff's office is a meaningless variable because it is the most recent date one is arrested, not the arrest date for all the offender information which follows. It is not uncommon, then, to have an arrest date later than a disposition date. This and other "quirks" result in confusion for researchers. Agencies should also be encouraged to streamline their data bases with an eye toward more use of this wealth of information. It would be better to have less entries more accurately available than the plethora of unusable variables. Coincidently, the recent efforts of the Bureau of Justice Statistics to promote and standardize research-compatible offender-based tracking systems in the states should be quite helpful.

The importance of effective crime control policy cannot be argued and structures must be developed to guide these processes. During implementation, however, policies are subject to the attitudes and interests of actors in all branches of government and at different levels. Conflict between the values of policy makers and policy implementors may hinder effective implementation, while convergent values can promote the spirit and intent as well as the letter of the law.

NOTES

1. Supervised release includes those on probation, parole, work furlough, mandatory release, or other legal releases from confinement.

2. For accessible treatments of time-series modeling and impact assessment, please see Cook and Campbell, 1979; McCain and McCleary, 1979; McDowall et al., 1980; McCleary and Hay, 1980.

3. Although the data sets purportedly ended in December, 1987, there was some doubt about the veracity of data for late 1987.

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TECHNICAL APPENDIX A:
PROBIT REGRESSION ANALYSIS

Probit regression analysis examines the relationship between a dichotomous dependent variable and one or more independent variables. The model which results from this analysis is known as the linear probability model. Probit analysis is appropriate when the behavior being measured is qualitative behavior as in the case of outcomes such as sentences to prison or probation. Use of Ordinary Least Squares (OLS) models are inappropriate in such cases since the incorrect assumption of linearity leads to estimates which 1) have no known distributional properties; 2) are sensitive to the range of the data; 3) may grossly understate the magnitude of the true effects; 4) systematically yield probability predictions outside the range of 0 and 1; and 5) get worse as the usual statistical improvements are made (Aldrich and Nelson, 1984).

Assumptions of the probit model are similar to those of the regression model except that the dependent variable is binary. Parameters are estimated with Maximum Likelihood Estimation (MLE). The conceptual difference between OLS and MLE is that OLS is concerned with finding parameter estimates that yield the smallest sum of squared errors in fitting a model to the data. MLE is concerned with picking parameter estimates of giving the highest probability of having obtained the observed Y.

Use of probit models is intuitively appealing because of their similarity to standard regression models. Most applied researchers have a working knowledge of regression techniques and would be able to apply this to learning probit regression without much difficulty.

The following is an example of a probit regression formula along with the coding of variables. This could be used as a guide for designing similar types of outcome analyses. StatPac Gold (David Walonick, 1987) is the statistical analysis package used in this research. It is a comprehensive general statistical package for microcomputers and is well-documented and easy to understand.

A probit model which examines the relationships among certain variables and those offenders who are sent to prison might be expressed in the following formula:

PRISON = RACE + PUBATTY + AGE + LAW + PLEABARG + TOTALTIM + SUPERVIS

Coding for the model is as follows:

"RACE"
1=Black
2=Mexican
3=White
9=Other

"PUBATTY"
0=Private Attorney
1=Public Defender
9=Propria Persona

"AGE"

"LAW" (Crime control law enacted July, 1982)
0=Before Law
1=After Law

"PLEABARG"
(Differences in count, charge, felony/misdemeanor, and dangerousness pleas)

"PRISON" (Prison sentence given)
0=No Prison
1=Prison Sentence

"TOTALTIM"
(Time from justice court start to superior court disposition)

"SUPERVIS" (Supervision status at time of original charge)
0=No Probation
1=Probation

Table A1.1
Computer Printout from StatPac Gold Statistical Analysis Package.

```
**************************************************************************
Probit Regression Analysis to Predict  "PLEABARG"  DIFF IN CNT CHG FM
DANG PLEAS--Before the Law
**************************************************************************
```

Variables in the Equation - Descriptive Statistics

VAR.	Variable label	MEAN:DV=0	MEAN:DV=1	STD. DEV.
DV14	DIFF IN CNT CHG FM DANG PLEAS			
V1	RACE	2.7016	2.7050	1.3518
V2	PUBATTY	0.8476	0.8033	0.5736
V3	AGE	25.6921	26.2720	8.8017
V4	SUPERVIS	0.1429	0.0649	0.2946
V5	ORIGINAL CHARGE DANGEROUSNESS	0.0571	0.1213	0.2946
V21	ORIGINAL CHARGE FILED IN SC	1.9016	1.8515	0.7150

```
Number of valid cases       =  793
Number of cases where DV=1  =  478
Number of cases where DV=0  =  315
Number of missing cases     =  111
Response percent            =  87.7%
Mean of dependent variable  =  0.60
```

Simple Correlation Matrix

	DV14	V1	V2	V3	V4	V5
V1	0.001					
V2	-0.038	-0.052				
V3	0.032	0.055	-0.075			
V4	-0.130	-0.062	0.019	-0.058		
V5	0.107	-0.024	-0.033	0.057	-0.048	
V21	-0.034	0.001	-0.032	-0.060	-0.065	-0.385

Probit Regression Coefficients

Var.	Coefficient	Std. Error	T-Ratio	Prob.
Constant	0.22846	0.23468	0.97352	0.33028
V1	-0.00616	0.03390	-0.18184	0.85569
V2	-0.06856	0.07970	-0.86029	0.38963
V3	0.00257	0.00524	0.49032	0.62393
V4	-0.52783	0.15403	-3.42672	0.00061
V5	0.49246	0.17780	2.76980	0.00562
V21	0.02534	0.06877	0.36851	0.71251

Log of likelihood function = -521.324179
Chi-square statistic for significance of equation = 22.93865
Degrees of freedom for chi-square statistic = 6
Significance level for chi-square statistic = 0.0008

****
Probit Regression Analysis to Predict "PLEABARG" DIFF IN CNT CHG FM DANG PLEAS--After the Law
****

Variables in the Equation - Descriptive Statistics

VAR.	Variable label	MEAN:DV=0	MEAN:DV=1	STD. DEV.
DV14	DIFF IN CNT CHG FM DANG PLEAS			
V1	RACE	2.6538	2.6769	1.3061
V2	PUBATTY	0.9231	0.8991	0.7013
V3	AGE	27.1987	26.4393	8.3294
V4	SUPERVIS	0.1074	0.0639	0.2762
V5	ORIGINAL CHARGE DANGEROUSNESS	0.0112	0.0971	0.2357
V21	ORIGINAL CHARGE FILED IN SC	2.0240	1.9591	0.7050

Number of valid cases = 1407
Number of cases where DV=1 = 783
Number of cases where DV=0 = 624
Number of missing cases = 272
Response percent = 83.8%
Mean of dependent variable = 0.56

Simple Correlation Matrix

	DV14	V1	V2	V3	V4	V5
V1	0.009					
V2	-0.017	-0.059				
V3	-0.045	-0.024	-0.032			
V4	-0.078	-0.041	-0.016	-0.033		
V5	0.181	0.039	-0.011	-0.019	-0.010	
V21	-0.046	-0.029	-0.011	0.008	-0.027	-0.347

Probit Regression Coefficients

Var.	Coefficient	Std. Error	T-Ratio	Prob.
Constant	0.26704	0.18177	1.46912	0.14179
V1	-0.00468	0.02642	-0.17729	0.85926
V2	-0.03157	0.04822	-0.65469	0.51269
V3	-0.00692	0.00408	-1.69629	0.08983
V4	-0.36635	0.12367	-2.96225	0.00306
V5	1.32187	0.20720	6.37978	0.00000
V21	0.03695	0.05080	0.72738	0.46700

Log of likelihood function = -932.631326
Chi-square statistic for significance of equation = 67.24706
Degrees of freedom for chi-square statistic = 6
Significance level for chi-square statistic = 0.0000

****
Probit Regression Analysis to Predict "PLEABARG" DIFF IN CNT CHG FM DANG PLEAS--Entire Sample
****

Variables in the Equation - Descriptive Statistics

VAR.	Variable label	MEAN:DV=0	MEAN:DV=1	STD. DEV.
DV14	DIFF IN CNT CHG FM DANG PLEAS			
V1	RACE	2.6699	2.6875	1.3226
V2	PUBATTY	0.8978	0.8628	0.6594
V3	AGE	26.6933	26.3759	8.5080
V4	SUPERVIS	0.1193	0.0642	0.2830
V5	ORIGINAL CHARGE DANGEROUSNESS	0.0266	0.1063	0.2590
V21	ORIGINAL CHARGE FILED IN SC	1.9830	1.9183	0.7107

Number of valid cases = 2200
Number of cases where DV=1 = 1261
Number of cases where DV=0 = 939
Number of missing cases = 383
Response percent = 85.2%
Mean of dependent variable = 0.57

Simple Correlation Matrix

	DV14	V1	V2	V3	V4	V5
V1	0.007					
V2	-0.026	-0.057				
V3	-0.018	0.006	-0.043			
V4	-0.096	-0.049	-0.006	-0.044		
V5	0.152	0.013	-0.023	0.010	-0.025	
V21	-0.045	-0.019	-0.012	-0.024	0.039	-0.364

Probit Regression Coefficients

Var.	Coefficient	Std. Error	T-Ratio	Prob.
Constant	0.26497	0.14255	1.85880	0.06307
V1	-0.00136	0.02077	-0.06570	0.94760
V2	-0.04637	0.04117	-1.12644	0.25996
V3	-0.00389	0.00319	-1.21878	0.22291
V4	-0.42342	0.09611	-4.40559	0.00001
V5	0.89302	0.13014	6.86208	0.00000
V21	0.02575	0.04071	0.63245	0.52711

Log of likelihood function = -1461.76400
Chi-square statistic for significance of equation = 79.02077
Degrees of freedom for chi-square statistic = 6
Significance level for chi-square statistic = 0.0000

TECHNICAL APPENDIX B:
TIME SERIES IMPACT ASSESSMENT

A time series is generally defined as a set of observations, ordered over time, representing a certain generating process. Time-series analysis presents a tool whereby the relationship among these observations may be deduced and a statistical model developed to describe the observed data.

Time-series analysis of the typed used in this research is based on the AutoRegressive Integrated Moving Average (ARIMA) modeling procedure popularized by Box and Jenkins (1976) and made more accessible to social science work by McCleary and Hay (1980). This approach to time-series analysis takes advantage of the idea that successive observations of a time series tend to be correlated; this correlation is termed serial correlation, or autocorrelation. Once the autocorrelation structure has been deduced, the time series may then be represented by a statistical model.

ARIMA modeling typically consists of three distinct stages:

1) *Identification* -- through graphs and statistics such as the AutoCorrelation Function (ACF) and the Partial AutoCorrelation Function (PACF), a possible model structure is identified;

2) *Estimation* -- using an appropriate maximum likelihood estimation algorithm, the model parameters are estimated along with their sampling statistics; and

3) *Diagnosis* -- the parameter estimates are tested for statistical significance, and the model residuals are analyzed and compared to a theoretical distribution, using the ACF, PACF, and other statistics.

If a tentative model fails the diagnostic tests, the model-building procedure returns to the Identification phase where any deficiencies are corrected. In practice, the strategy above will usually lead to a suitable, statistically-sound model.

The time series impact assessment, or the interrupted time-series quasi-experiment, is concerned with the effects of a specific change in the environment. For example, using notation set forth by Campbell and Stanley (1966), a time series impact assessment diagram would be:

$$O_1\ O_2\ O_3\ O_4\ O_5\ O_6\ O_7\ O_8\ X\ O_9\ O_{10}\ O_{11}\ O_{12}\ O_{13}\ O_{14}\ O_{15}\ O_{16}$$

where each O_n is a time-series observation and X represents a *discrete* intervention. For this research, the O_n would be a time series of one of the court process variables while the X would stand for the enactment of A.R.S. 13-604.01.

The design of the time series impact assessment is structured to address the issues of:

1) Did the intervention actually produce an impact on the time series?

2) If the intervention did produce an impact, was the *onset*, or beginning, immediate or gradual?

3) Was the duration of the impact permanent or temporary?

In this section, the impact models for the felony class reduction series (see Figure 3b) are built as examples. The analysis is presented step by step with discussion of the important points to be considered at each step. The purpose of this analysis is to determine if enactment of A.R.S. 13-604.01 produced an impact in the proportion of cases where the original offense felony class was reduced between case filing and disposition. Although the data of interest are those representing offenders who were on probation at the time the current offense was committed, ARIMA models were also built and analyzed for the group of offenders who were *not* on probation. Analysis of these data provide a crucial comparison between the "treatment," or experimental, and the "no treatment," or control groups; any effects due strictly to A.R.S. 13-604.01 should be present for the probation group and not present for the non-probation group. We do not, in the interest of brevity, present the results of the non-probation analysis (as should be expected, however, we found that A.R.S. 13-604.01 produced no statistically significant impact on this group).

Identification

Identification typically begins with a visual inspection of a plot of the raw data over time. Such a plot for this series was shown in Figure 3b. The time plot provides valuable information regarding possible "non-stationarity" in both the level and the variance of the series. For impact assessments, the time-series segments on either side of the intervention can also provide evidence of the magnitude and onset of any impact.

Table A2.1 and Figure A2.1 present the ACF and PACF, with plots, of the raw felony class reduction data.

Table A2.1
ACF and PACF

AUTOCORRELATION

1- 12	.73	.73	.71	.70	.62	.59	.58	.60	.50	.49	.47	.44
ST.E.	.10	.14	.17	.20	.22	.24	.25	.26	.27	.28	.29	.30
Q	57.8	116	172	227	270	310	349	391	421	449	476	499
13- 24	.41	.37	.41	.34	.32	.30	.29	.25	.22	.23	.23	.20
ST.E.	.30	.31	.31	.32	.32	.32	.33	.33	.33	.33	.33	.34
Q	520	537	558	572	585	597	608	616	623	630	637	643

PARTIAL AUTOCORRELATION

1- 12	.73	.42	.25	.18	-.07	-.05	.05	.16	-.11	-.07	-.03	-.01
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10
13- 24	.05	-.04	.12	-.11	-.01	-.01	-.00	-.02	-.06	.06	.05	.06
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10

Figure A2.1
Plots of ACF and PACF

AUTOCORRELATION

```
          -1.0  -.8  -.6  -.4  -.2   .0   .2   .4   .6   .8  1.0
           +----+----+----+----+----+----+----+----+----+----+----+
                                      I
  1   .73                       +    IXXXX+XXXXXXXXXXXXX
  2   .73                     +      IXXXXXX+XXXXXXXXXXX
  3   .71                    +       IXXXXXXX+XXXXXXXXXX
  4   .70                  +         IXXXXXXXXX+XXXXXXX
  5   .62                 +          IXXXXXXXXXX+XXXX
  6   .59                +           IXXXXXXXXXXX+XXX
  7   .58                +           IXXXXXXXXXXX+XXX
  8   .60               +            IXXXXXXXXXXXX+XX
  9   .50               +            IXXXXXXXXXXXXX
 10   .49              +             IXXXXXXXXXXXX +
 11   .47              +             IXXXXXXXXXXXX +
 12   .44             +              IXXXXXXXXXXX   +
 13   .41             +              IXXXXXXXXXX    +
 14   .37             +              IXXXXXXXXX     +
 15   .41             +              IXXXXXXXXXX    +
 16   .34            +               IXXXXXXXX       +
 17   .32            +               IXXXXXXXX       +
 18   .30            +               IXXXXXXXX       +
 19   .29            +               IXXXXXXX        +
 20   .25            +               IXXXXXX         +
 21   .22            +               IXXXXX          +
 22   .23            +               IXXXXXX         +
 23   .23            +               IXXXXXX         +
 24   .20            +               IXXXXX          +
```

PARTIAL AUTOCORRELATION

```
          -1.0  -.8  -.6  -.4  -.2   .0   .2   .4   .6   .8  1.0
           +----+----+----+----+----+----+----+----+----+----+----+
                                      I
  1   .73                       +    IXXXX+XXXXXXXXXXXXX
  2   .42                       +    IXXXX+XXXXX
  3   .25                       +    IXXXX+X
  4   .18                       +    IXXXX+
  5  -.07                       +  XXI    +
  6  -.05                       +   XI    +
  7   .05                       +    IX   +
  8   .16                       +    IXXXX+
  9  -.11                       + XXXI    +
 10  -.07                       +  XXI    +
 11  -.03                       +   XI    +
 12  -.01                       +    I    +
 13   .05                       +    IX   +
 14  -.04                       +   XI    +
 15   .12                       +    IXXX +
```

```
16   -.11                    + XXXI    +
17   -.01                    +    I    +
18   -.01                    +    I    +
19    .00                    +    I    +
20   -.02                    +   XI    +
21   -.06                    +  XXI    +
22   _.06                    +    IXX  +
23    .05                    +    IX   +
24    .06                    +    IX   +
```

An ACF pattern like the one shown above indicates a non-stationary, integrated time series. This type of non-stationarity is easily handled by "differencing" the time series, or subtracting successive observations from each other to obtain a new series. For example, if we denote a differenced time series by Z_t and the undifferenced time series by Y_t, then the relationship between them is:

$$Z_t = Y_{t+1} - Y_t$$

The following table and graph, Table A2.2 and Figure A2.2, show the ACF and PACF for the differenced felony class reduction series.

Table A2.2
ACF and PACF

AUTOCORRELATION

1- 12	-.53	.04	-.01	.12	-.08	-.08	-.01	.19	-.12	-.01	.03	.00
ST.E.	.11	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12
Q	30.5	30.7	30.7	32.3	33.0	33.7	33.7	38.0	39.7	39.7	39.8	39.8
13-24	.04	-.17	.22	-.10	.02	-.01	.01	.02	-.08	.01	.06	-.05
ST.E.	.13	.13	.13	.13	.13	.13	.13	.13	.13	.14	.14	.14
Q	40.0	43.6	49.5	50.9	50.9	51.0	51.0	51.0	51.9	51.9	52.4	52.7

PARTIAL AUTOCORRELATION

1- 12	-.53	-.34	-.26	-.01	.03	-.12	-.25	.01	.06	.04	.03	-.06
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10
13- 24	.03	-.14	.08	.03	.02	.03	-.03	.02	-.09	-.08	-.08	-.07
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10

Figure A2.2
Plots of ACF and PACF

AUTOCORRELATION

```
          -1.0  -.8  -.6  -.4  -.2   .0   .2   .4   .6   .8  1.0
            +----+----+----+----+----+----+----+----+----+----+----+
                                      I
  1   -.53                XXXXXXXX+XXXXI    +
  2    .04                       +     IX    +
  3   -.01                       +     I     +
  4    .12                       +     IXXX  +
  5   -.08                       +   XXI     +
  6   -.08                       +   XXI     +
  7   -.01                       +     I     +
  8    .19                       +     IXXXXX+
  9   -.12                       +  XXXI     +
 10   -.01                       +     I     +
 11    .03                       +     IX    +
 12    .00                       +     I     +
 13    .04                       +     IX    +
 14   -.17                       + XXXXI     +
 15    .22                       +     IXXXXX+
 16   -.10                      +   XXXI      +
 17    .02                      +     IX      +
 18   -.01                      +     I       +
 19    .01                      +     I       +
 20    .02                      +     I       +
 21   -.08                      +    XXI      +
 22    .01                      +     I       +
 23    .06                      +     IXX     +
 24   -.05                      +    XI       +
```

PARTIAL AUTOCORRELATION

```
          -1.0  -.8  -.6  -.4  -.2   .0   .2   .4   .6   .8  1.0
            +----+----+----+----+----+----+----+----+----+----+----+
                                      I
  1   -.53                XXXXXXXX+XXXXI    +
  2   -.34                    XXXX+XXXXI    +
  3   -.26                      XX+XXXXI    +
  4   -.01                        +    I    +
  5    .03                        +    IX   +
  6   -.12                        + XXXI    +
  7   -.25                       X+XXXXI    +
  8    .01                        +    I    +
  9    .06                        +    IX   +
 10    .04                        +    IX   +
 11    .03                        +    IX   +
 12   -.06                        +  XXI    +
 13    .03                        +    IX   +
 14   -.14                       +XXXXI    +
 15    .08                        +    IXX  +
```

16	.03	+	IX +
17	.02	+	IX +
18	.03	+	IX +
19	-.03	+	XI +
20	.02	+	IX +
21	-.09	+	XXI +
22	-.08	+	XXI +
23	-.08	+	XXI +
24	-.07	+	XXI +

After the first differencing operation, the time series now appears to be stationary.

A pattern as shown in Figure A2.2, with a single spike (at lag 1) in the ACF, indicates a Moving Average component. As a tentative model, then, we will use:

$$Y_t = \Theta_0 + \frac{(1 - \Theta_1 B)}{(1 - B)} a_t$$

Estimation

Using a suitable non-linear, maximum likelihood estimation procedure (Liu and Hudak, 1986) the two parameters of the model are estimated, and the results are presented below.

Table A2.3
Summary for Univariate Time-Series Model

PARAMETER LABEL	NUM./ DENOM.	FACTOR	ORDER	CONS-TRAINT	VALUE	STD ERROR	T VALUE
Constant	CNST	1	0	NONE	.0024	.0017	1.48
Moving Average	MA	1	1	NONE	.7395	.0649	11.39

TOTAL SUM OF SQUARES	.135939E+01
TOTAL NUMBER OF OBSERVATIONS	106
RESIDUAL SUM OF SQUARES.	.423685E+00
R-SQUARE	.685
EFFECTIVE NUMBER OF OBSERVATIONS . .	105
RESIDUAL VARIANCE ESTIMATE	.403510E-02
RESIDUAL STANDARD ERROR.	.635224E-01

The moving average parameter is statistically significant, but the constant term (estimation of series trend) is not. Therefore, the constant term is dropped and the moving average parameter reestimated.

Table A2.4
Summary for Univariate Time-Series Model

PARAMETER LABEL	NUM./ DENOM.	FACTOR	ORDER	CONS-TRAINT	VALUE	STD ERROR	T VALUE
Moving Average	MA	1	1	NONE	.7147	.0688	10.39

TOTAL SUM OF SQUARES	.135939E+01
TOTAL NUMBER OF OBSERVATIONS	106
RESIDUAL SUM OF SQUARES.	.431701E+00
R-SQUARE	.679
EFFECTIVE NUMBER OF OBSERVATIONS . .	105
RESIDUAL VARIANCE ESTIMATE	.411144E-02
RESIDUAL STANDARD ERROR.	.641205E-01

As the moving average parameter estimate is statistically significant, the analysis now moves to diagnosis.

Diagnosis

Model diagnosis is concerned with any remaining autocorrelation within the residuals of the model. The first step is to compute the ACF and PACF for the residual series.

Table A2.5
ACF and PACF

AUTOCORRELATION

1- 12	-.10	.02	.05	.11	-.09	-.12	.02	.19	-.05	-.03	.02	-.00
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.11	.11	.11	.11
Q	1.2	1.2	1.5	2.8	3.7	5.3	5.3	9.6	10.0	10.1	10.1	10.1
13- 24	-.02	-.12	.16	-.05	-.01	-.04	-.03	-.06	-.14	-.05	.03	-.03
ST.E.	.11	.11	.11	.11	.11	.11	.11	.11	.11	.11	.11	.11
Q	1.2	1.2	1.5	2.8	3.7	5.3	5.3	9.6	10.0	10.1	10.1	10.1

PARTIAL AUTOCORRELATION

1- 12	-.10	.00	.05	.12	-.07	-.15	-.02	.21	.03	-.03	-.04	-.06
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10
13- 24	.03	-.06	.14	-.06	-.03	-.04	-.08	-.05	-.13	-.03	-.02	.01
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10

Figure A2.3
Plots of ACF and PACF

AUTOCORRELATION

```
          -1.0  -.8  -.6  -.4  -.2   .0   .2   .4   .6   .8  1.0
           +----+----+----+----+----+----+----+----+----+----+----+
                                         I
  1   -.10                          + XXXI    +
  2    .02                          +    I    +
  3    .05                          +    IX   +
  4    .11                          +    IXXX +
  5   -.09                          +  XXI    +
  6   -.12                          + XXXI    +
  7    .02                          +    I    +
  8    .19                          +    IXXXXX
  9   -.05                          +   XI    +
 10   -.03                          +   XI    +
 11    .02                          +    IX   +
 12    .00                          +    I    +
 13   -.02                          +    I    +
 14   -.12                          + XXXI    +
 15    .16                          +    IXXXX+
 16   -.05                          +   XI    +
 17   -.01                          +    I    +
 18   -.04                          +   XI    +
 19   -.03                          +   XI    +
 20   -.06                          +  XXI    +
 21   -.14                          +XXXXI    +
 22   -.05                          +   XI    +
 23    .03                          +    IX   +
 24   -.03                          +   XI    +
```

PARTIAL AUTOCORRELATION

```
          -1.0  -.8  -.6  -.4  -.2   .0   .2   .4   .6   .8  1.0
           +----+----+----+----+----+----+----+----+----+----+----+
                                         I
  1   -.10                          + XXXI    +
  2    .00                          +    I    +
  3    .05                          +    IX   +
  4    .12                          +    IXXX +
  5   -.07                          +  XXI    +
  6   -.15                          +XXXXI    +
  7   -.02                          +   XI    +
  8    .21                          +    IXXXXX
  9    .03                          +    IX   +
 10   -.03                          +   XI    +
 11   -.04                          +   XI    +
 12   -.06                          +   XI    +
 13    .03                          +    IX   +
 14   -.06                          +  XXI    +
 15    .14                          +    IXXXX+
```

```
16   -.06                    +   XI    +
17   -.03                    +   XI    +
18   -.04                    +   XI    +
19   -.08                    +  XXI    +
20   -.05                    +   XI    +
21   -.13                    + XXXI    +
22   -.03                    +   XI    +
23   -.02                    +    I    +
24    .01                    +    I    +
```

At minimum, an adequately constructed ARIMA model should have no significant spikes at either lag 1 or lag 2--as indicated in Figure A2.3--nor at the seasonal lags (12, 24, etc. for monthly data). Furthermore, the residuals should be uncorrelated. This is tested with a Q statistic--shown as the third line for each row of ACF--which is distributed as a chi-square variable with degrees of freedom:

$$df = N - k$$

where N is the number of ACF estimated and k is the number of parameters in the model. For this model, $Q_{23} = 19.5$, which is *not* statistically significant.

This model is acceptable and the analysis now turns to the impact assessment component.

Impact Assessment

Before beginning the analysis, an "impact variable" must first be constructed. This is easily conceptualized as a dummy variable with a value of 0 prior to the intervention and a value of 1 after the intervention. By denoting the impact variable as I_t, the new model structure is given by:

$$Y_t = I_t + \frac{(1 - \Theta_1 B)}{(1 - B)} a_t$$

Since the law became effective in late July, 1982, the impact variable takes on the values:

$$I_t = 0 \text{ for lags } 1 - 43, \text{ and}$$
$$I_t = 1 \text{ for lags } 44 - 106.$$

Finally, the pattern of impact must be specified. The law became effective in July, 1982, but the impact would only be felt on cases disposed *after* that date. A gradual pattern of impact is hypothesized and the full model is given by:

$$Y_t = \frac{w_0}{(1 - d_1 B)} I_t + \frac{(1 - \Theta_1 B)}{(1 - B)} a_t$$

Table A2.6
Summary for Univariate Time-Series Model

PARAMETER LABEL	NUM./ DENOM.	FACTOR	ORDER	CONS-TRAINT	VALUE	STD ERROR	T VALUE
Impact Level	NUM	1	0	NONE	.0393	.0134	2.94
Impact Rate	DENM	1	1	NONE	.8080	.0688	11.75
Moving Average	MA	1	1	NONE	.8483	.0473	17.95

TOTAL SUM OF SQUARES	.135939E+01
TOTAL NUMBER OF OBSERVATIONS	106
RESIDUAL SUM OF SQUARES.	.383626E+00
R-SQUARE	.715
EFFECTIVE NUMBER OF OBSERVATIONS . .	105
RESIDUAL VARIANCE ESTIMATE	.365358E-02
RESIDUAL STANDARD ERROR.	.604449E-01

Both the Impact Level (w_0) and the Impact Rate (d_1) parameters are statistically significant. The enactment of the law produced a gradual, permanent impact on the proportion of probation cases in which the offense felony class was reduced.

Summary

This section presented a step-by-step--although simplified--procedure for building an ARIMA time-series model and for extending that basic model to include "intervention analysis" or "impact assessment."

By definition, impact assessment and the attribution of causation to any one factor is much more complex than the process presented here. The interrupted time-series quasi-experiment, however, controls for most of the threats to internal validity (see Campbell and Stanley, 1966) and, with the introduction of a control series, allows the inference of "impact/no impact" to be drawn with more confidence than alternative tests.