CRIME PREDICTION FOR WASHINGTON STATE

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PREFACE

In the decade prior to 1974, Washington State and the nation experienced the greatest increase in crime rate and volume in the history of recorded crime. Is this unprecedented growth of crime continuing? The purpose of this document is to predict what might reasonably be expected to occur in terms of future crime for Washington State. The importance of this type of forecasting is based upon the necessity to plan for the orderly allocation of public resources for both local and state criminal justice agencies. The prediction of future crime in this document better enables us to address the issues of public safety and judicial and correctional management.

Documents of this nature represent the Office of Financial Management's commitment for the pursuit of improved decision-making methods. Those methods that produce results which more closely depict reality will also, hopefully, provide the potential for more pragmatic and cost-effective decisions.

We welcome comments on the content and format of this document. We also wish to acknowledge the valuable contribution of those who critically reviewed this document. The publication and forecasts were prepared in the Statistical Analysis Center, Office of Financial Management, Division of Criminal Justice, by John P. O'Connell.

M. Lyle Jacobsen, Director
Office of Financial Management
August, 1980

ERRATA

PAGE	ERROR	CORRECTIONS
1	aggrevated	aggravated
18	cohort efforts	cohort effects

CONTENTS

CRIME PREDICTION FOR WASHINGTON STATE

The future volume and rate of crime are important factors for the government operations as well as for the quality of our daily lives. The purpose of this study is to predict what might reasonably be expected in terms of the future crime patterns in Washington State. Obviously, no attempts at predictions guarantee future occurrences, however, the need to make such efforts must be undertaken if responsible decisions are to be made in government.

Part I of this study reports the predicted crime rates and volume of crime for Washington State. Crime rates and volume are reported by three categories, total crime, violent crime, and property crime. Violent crime includes the combinations of murder, manslaughter, robbery, rape, and aggrevated assault. Property crime includes burglary, auto theft, and larceny. Total crime includes the combination of all the above listed types of crime. The measurement used for crime in this study is reported crime for Washington State as published in the Crime in United States 1961 to 1978.

Part II of this study provides the justification for the method used for predicting crime and crime rates. The major point argued in this section is that the crime rate, which has shown a striking monotonic increase between 1961 and 1974, has stabilized. Moreover, it is argued that until there is another social change similar in magnitude of the changes in the late 60's and early 70's the crime rate on average will remain stable.

With the realization of a stabilizing crime rate, the prediction of the future volume of crime becomes quite simple. Assuming that the crime rate is stable for the near future, the major factor influencing crime rate is the size of the state's population. However, the simplicity of the forecasting model proposed here should not be mistaken for an uninformed approach. The background and the rationale for such a predictive method is well documented in Part II.

PART I

PREDICTED CRIME RATES AND THE VOLUME OF CRIME FOR WASHINGTON STATE

This part of the study reports the predicted crime rates and volume of crime for Washington State for 1979 to 2000. As will be noted in Part II of this study, and as is true of all scientific forecasts or predictions, the further one gets from the present, the less confidence one should have in predictions. Therefore, in this study, the predictions for 1980 to 1985 should be accepted with more confidence than the predictions for 1990, 1995, and 2000.

Crime rates and volume of crime are reported in three categories -- total crime, violent crime, and property crime. Violent crime includes the combinations of murder, manslaughter, robbery, rape and aggravated assault. Property crime includes burglary, auto theft, and larceny. Total crime includes the combination of all of the above listed crime. The measurement used for crime in this study is reported crime for Washington State as published for Washington State in Crime in United States, 1961 to 1978.

Crime rates for this study are based on the at-risk population of males between the ages of 15 and 34 in the Washington State population. Historically, this subpopulation has been responsible for the vast majority of crime. Clearly such a technique discounts the influence of female and older male crime behavior, but the limited volume of crime committed by these other subpopulations does not warrant their inclusion in the methodology for crime rate predictions. Justifying data for the strategy of using the at-risk group of males 15 to 34 can be found in Appendix I.

RESULTS

As the crime rate table and charts indicate the crime rate in Washington State increased rapidly between the early 1960's and 1974. Apparently, since this time, both violent and property crime rates have leveled off. The highest property crime rate in 1974 was 32.9 crimes per 100 at risk persons (i.e., males between 15 and 34). The highest violent crime rate occurred in 1975 at 2.23 crimes per 100 at-risk group persons. In both cases the peak represents a drastic increase compared to the 1961 crime rates. During this period of time property crimes for at-risk persons increased 22.2 per 100, and violent crimes for at-risk persons increased 1.8 crimes per 100.

Based on the rationale developed in Part II of this study, it is predicted that -- within an expected range of variation -- the crime rate will remain stable. It is expected that the total crime rate, plus or minus 3.2 crimes per 100 at-risk persons will remain near an average of 33.3 crimes per 100 at-risk persons. Violent crimes are expected to stablize around 2.1 crimes per 100 at-risk persons plus or minus .0019 crimes per 100 at-risk persons. Property crimes are expected to stablize around 30.8 crimes per 100 at-risk persons plus or minus 3.2 per 100 at-risk persons.

As was noted above, the number of years that the crime rate will remain stable is unknown. Another characteristic of the uncertainty of crime rates is the direction that future changes may take. It is possible, given a significant social change, for the crime rate to enter into either an increasing or a decreasing trend. However, once a trend had begun -- on the basis of previous history and the theoretical assumptions of the social diffusion model (see Part II) -- it is expected that the trend will continue for a five to ten year period.

For instance, recent history has shown that the major cities in Washington State experienced an increase in the crime rate during World War II. Following the war there was a decreasing trend in these cities' crime rates. Then through the 1950's and early 1960's the crime rate remained relatively stable until the surge of the late 1960's and early 1970's.

As the tables and charts for the volume of crime indicate, the number of future crimes is expected to grow each year, except for a small dip in 1995, until the year 2000. This is the case, even though the crime rate is assumed to have stabilized. The reason for this expected increase in the number of crimes is the continued growth in the at-risk population in the state.

The predicted number of crimes are presented in the following charts and tables as the mean expected number of crimes and a high and low range of expected crimes. As shown in these displays, the predicted mean level of expected total crime in 1980 is 258,308 with a low range of 220,936 and a high range of 268,068. Except for the small dip in 1995, the number of total crimes is expected to increase gradually until the year 2000. In the year 2000 the number of crimes is expected to reach 294,404 with a low range of 266,028 and a high range of 322,780.

In 1980, the predicted mean level of property crime is 229,037 with a low range of 217,072 and a high range of 266,867. In the year 2000 expected number of property crimes is 275,782 with a low range of 247,406 and a high range of 304,158.

Violent crimes, in 1980, are expected to be at a mean of 16,399 with a low range of 14,783 and a high range of 17,895. In the year 2000 violent crimes are expected to increase 18,202 with a low possible range of 16,468 and a high range of 19,935.

TOTAL, VIOLENT, AND PROPERTY CRIME RATES FOR MALES 15-34
FOR WASHINGTON STATE 1961 - 1978 AND PREDICTED
MEAN CRIME RATES AND EXPECTED RANGE FOR 1979 - 1985, 1990, 1995, and 2000

	YEAR	TOTAL CRIME RATES	VIOLENT CRIME RATES	PROPERTY CRIME RATES
ACTUAL	1961	.110	.0043	.107
	1962	.117	.0047	.112
	1963	.121	.0048	.116
	1964	.141	.0064	.134
	1965	.138	.0072	.131
	1966	.154	.0082	.145
	1967	.181	.0099	.171
	1968	.222	.0135	.209
	1969	.285	.0157	.269
	1970	.296	.0140	.282
	1971	.292	.0148	.277
	1972	.292	.0154	.277
	1973	.304	.0162	.287
	1974	.349	.0201	.329
	1975	.350	.0223	.328
	1976	.324	.0217	.302
	1977	.312	.0204	.292
	1978	.329	.0218	.308

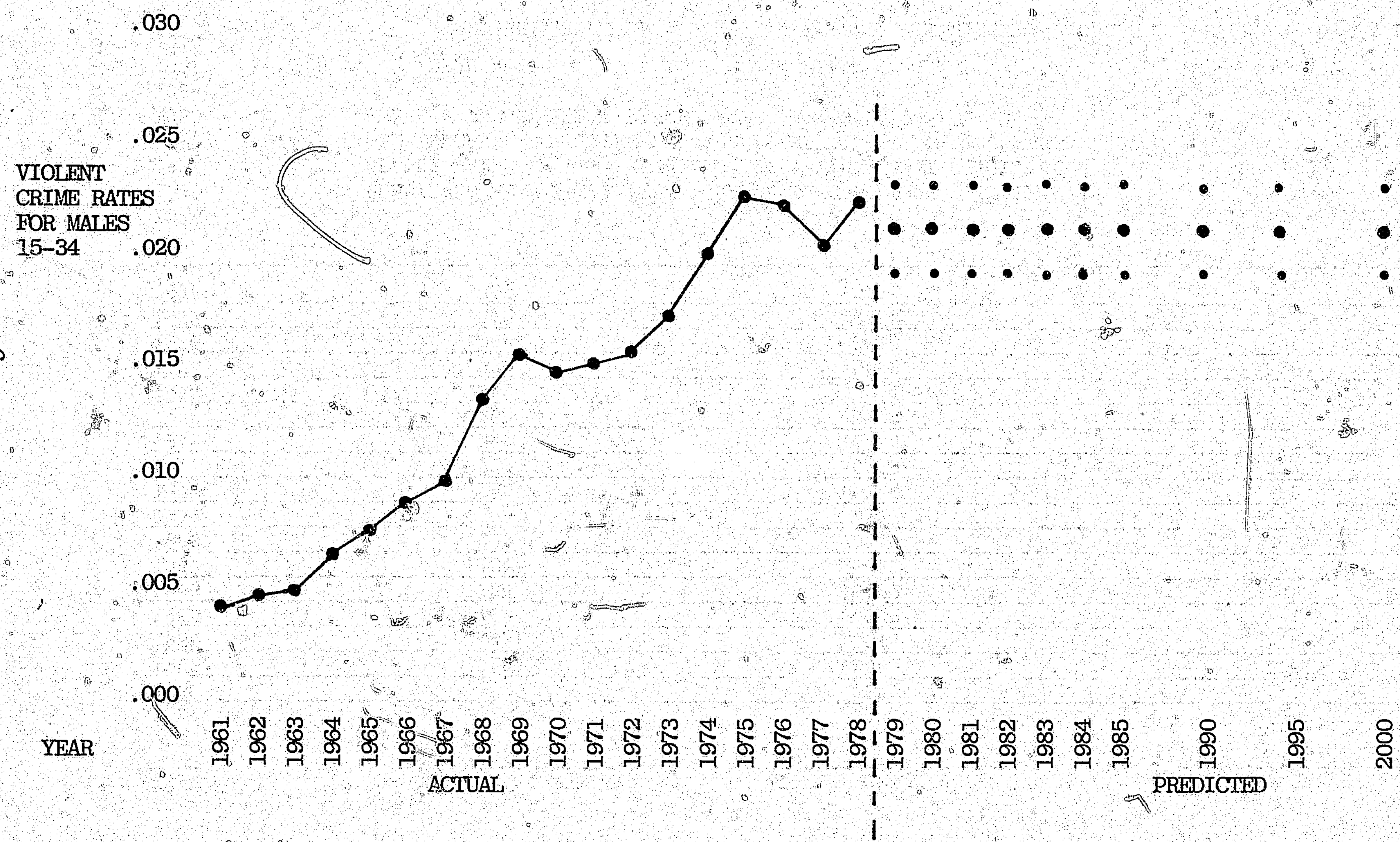
PREDICTED

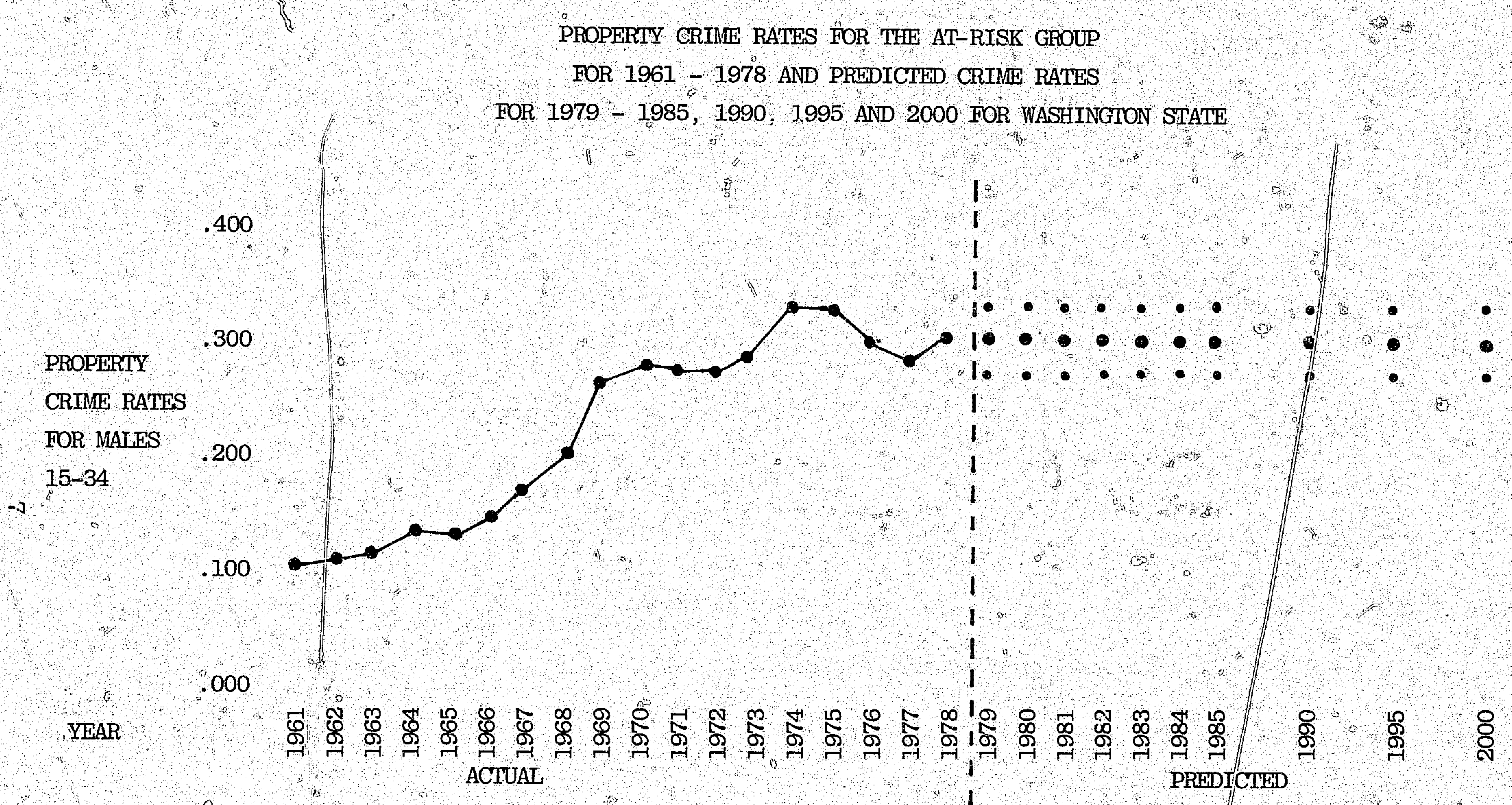
1979
1980
1981
1982
1983
1984
1985
1990
1995
2000

PREDICTED MEAN AND EXPECTED RANGE IS CALCULATED AS THE MEAN OF THE RATES BETWEEN 1974 AND 1978. THIS TIME PERIOD IS USED BECAUSE IT REPRESENTS THE ASYMPTOTE OF THE DIFFUSION CURVE. THE EXPECTED RANGE OF DEVIATION IS 2(SD).

TOTAL CRIME RATES	VIOLENT CRIME RATES	PROPERTY CRIME RATES
MEAN =.333	MEAN = .0213	MEAN = .308
STANDARD DEVIATION = .016	STANDARD DEVIATION = .00095	STANDARD DEVIATION = .016

VIOLENT CRIME RATES FOR THE AT-RISK GROUP
FOR 1961 - 1978 AND PREDICTED CRIME RATES
FOR 1979 - 1985, 1990, AND 2000 FOR WASHINGTON STATE




PROPERTY CRIME RATES FOR THE AT-RISK GROUP
FOR 1961 - 1978 AND PREDICTED CRIME RATES
FOR 1979 - 1985, 1990, 1995 AND 2000 FOR WASHINGTON STATE
PROPERTY
CRIME RATES
FOR MALES
15-34
.400
.300
.200
.100
.000
YEAR
1961
1962
1963
1964
1965
1966
1967
1968
1969
1970
1971
1972
1973
1974
1975
1976
1977
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1979
1980
1981
1982
1983
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1985
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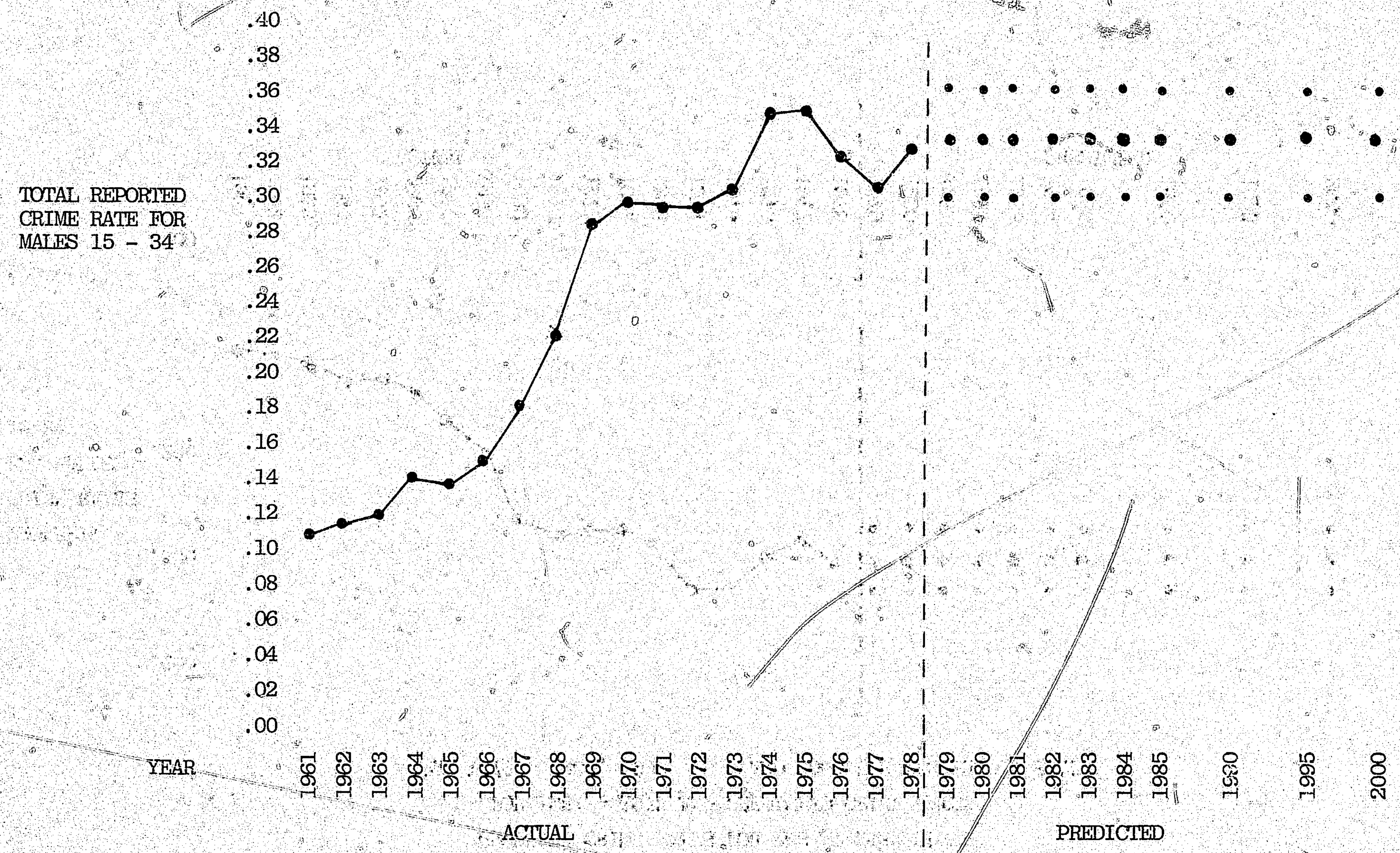
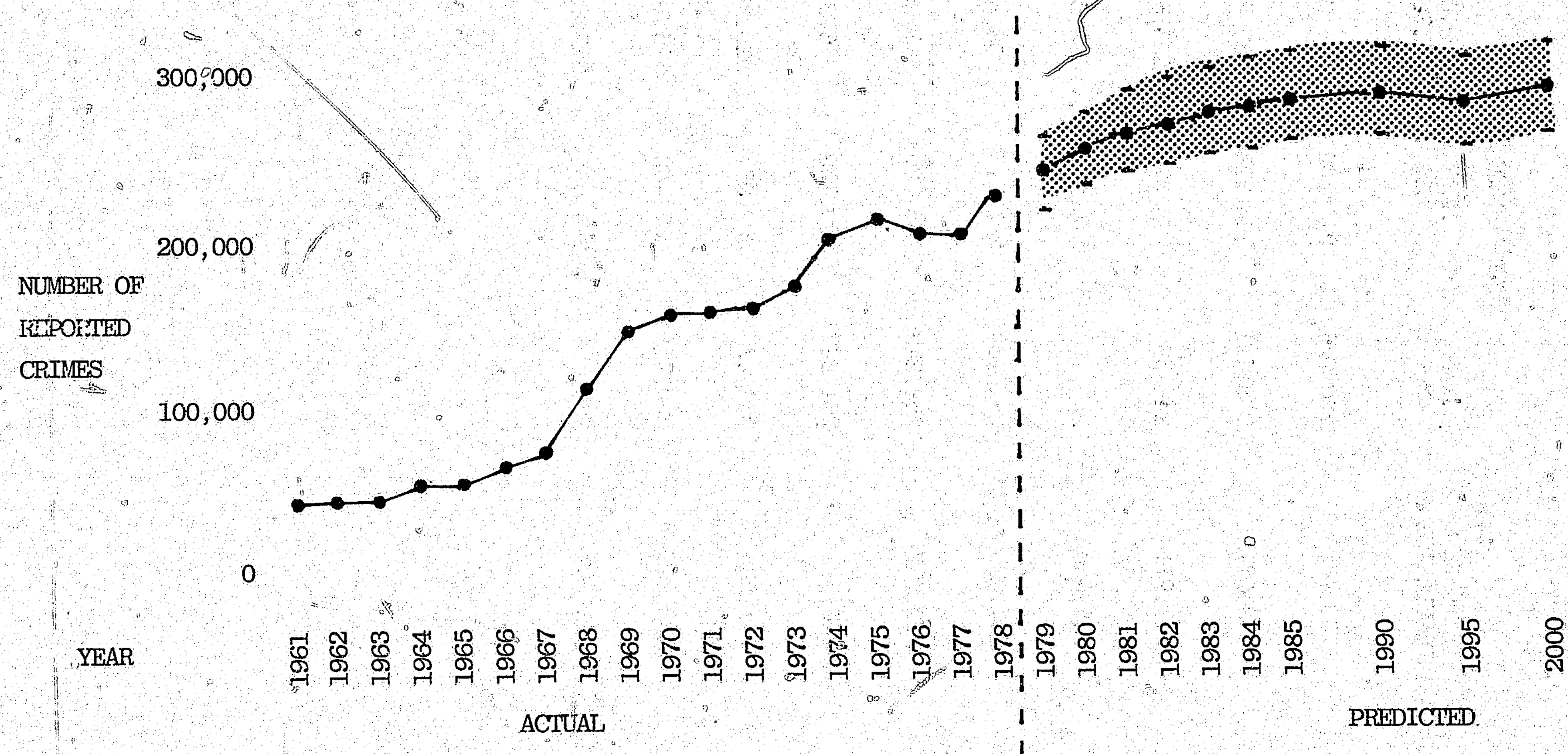
1995
2000
ACTUAL
PREDICTED

TOTAL CRIME RATES FOR THE AT-RISK GROUP FOR 1961 - 1978 AND
PREDICTED CRIME RATES FOR 1979 - 1985,
1990, 1995, AND 2000 FOR WASHINGTON STATE



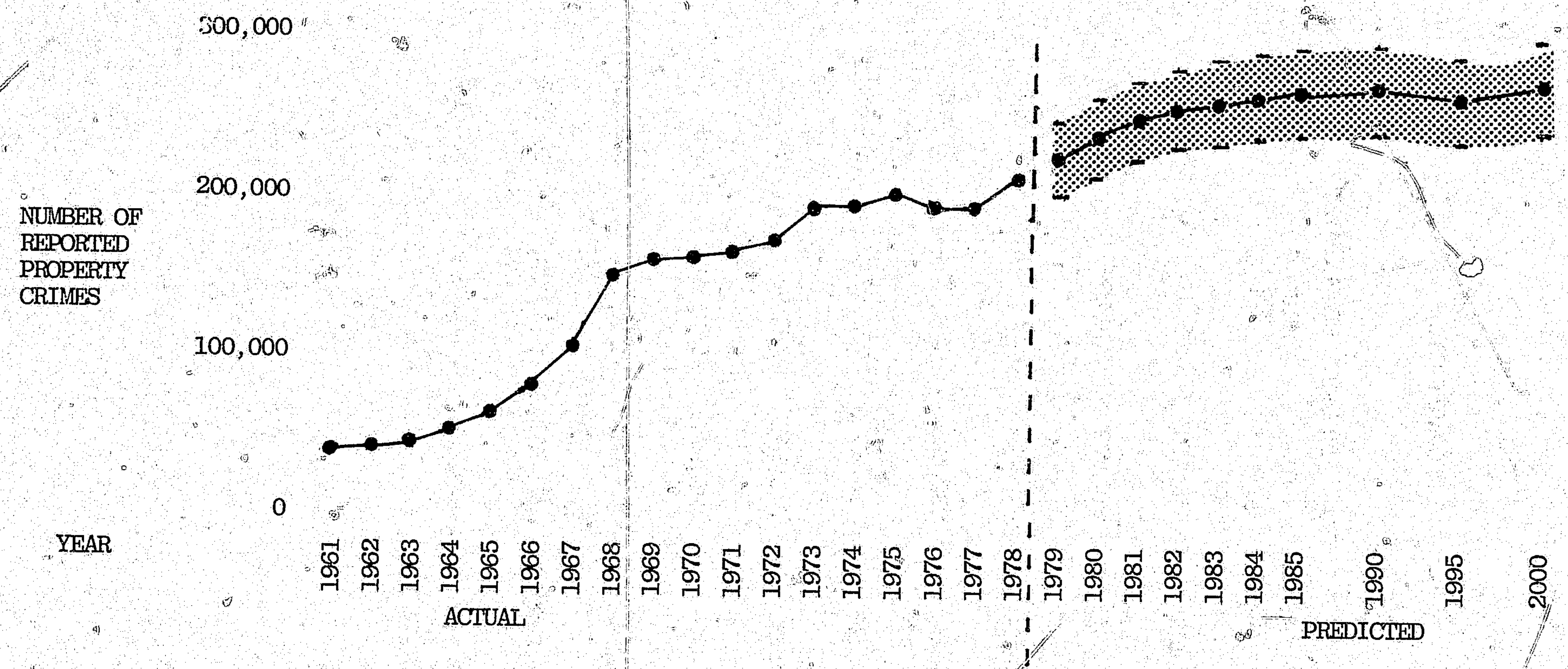
ACTUAL VOLUME OF TOTAL REPORTED CRIME FOR 1961 - 1978
AND THE PREDICTED VOLUME OF TOTAL REPORTED CRIME
FOR 1979 - 1985, 1990, 1995 AND 2000 FOR WASHINGTON STATE



TOTAL CRIME

YEAR	AT-RISK POPULATION	TOTAL CRIME RATES LOW .300	MEAN .332	HIGH .364
1979	736,453	220,936	244,502	268,068
1980	778,037	238,411	258,308	283,205
1981	811,971	243,591	269,574	295,557
1982	832,036	249,610	276,235	302,861
1983	847,026	254,108	281,212	308,318
1984	860,722	258,216	285,760	313,303
1985	870,874	261,262	289,130	316,998
1990	881,585	264,475	292,687	320,897
1995	865,848	259,754	287,462	315,169
2000	886,759	266,028	294,404	322,780

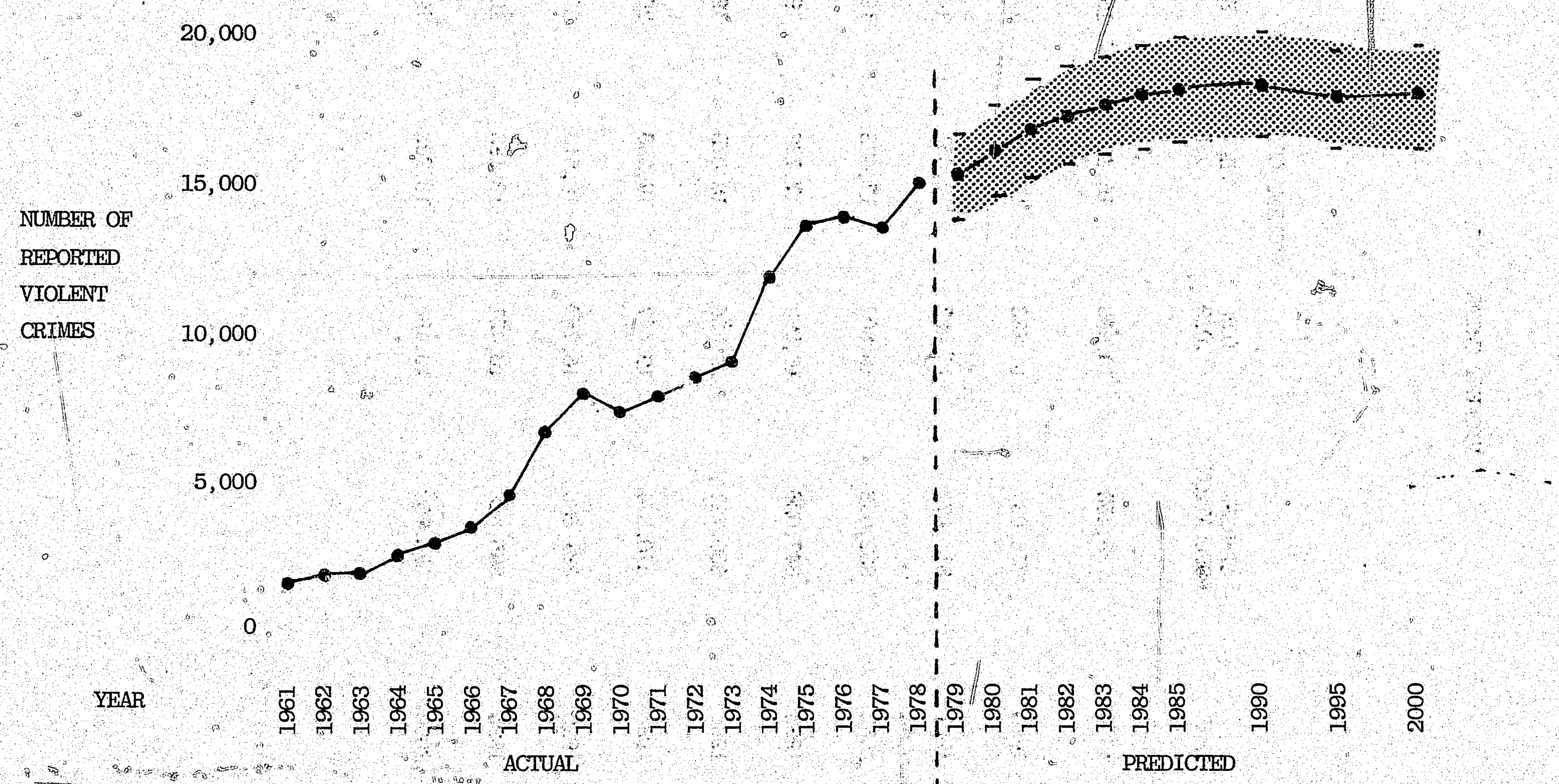
ACTUAL VOLUME FOR REPORTED PROPERTY CRIME FOR 1961 - 1978
AND THE PREDICTED VOLUME OF REPORTED PROPERTY CRIME
FOR 1979 - 1985, 1990, AND 2000 FOR WASHINGTON STATE



PROPERTY CRIME

		PROPERTY CRIME RATES		
YEAR	AT-RISK POPULATION	LOW .279	MEAN .311	HIGH .343
1979	736,453	205,470	229,037	252,603
1980	778,031	217,072	241,969	266,867
1981	811,971	226,540	252,523	278,506
1982	832,036	232,138	258,763	285,388
1983	847,026	236,320	263,425	290,530
1984	860,722	240,141	267,684	295,228
1985	870,874	242,974	270,842	298,710
1990	881,588	245,962	274,173	302,384
1995	865,848	241,572	269,278	296,985
2000	886,759	247,406	275,782	304,158

ACTUAL VOLUME FOR REPORTED VIOLENT CRIMES FOR 1961 - 1978
AND THE PREDICTED VOLUME OF REPORTED VIOLENT CRIMES
FOR 1979-1985, 1990 AND 2000 FOR WASHINGTON STATE



VIOLENT CRIME

YEAR	AT-RISK POPULATION	VIOLENT CRIME RATES LOW .019	MEAN .021	HIGH .023
1979	736,453	13,993	15,466	16,938
1980	778,037	14,783	16,339	17,895
1981	811,971	15,427	17,051	18,675
1982	832,036	15,808	17,473	19,137
1983	847,026	16,093	17,788	19,482
1984	860,722	16,354	18,075	19,797
1985	870,874	16,547	18,288	20,030
1990	881,585	16,750	18,513	20,276
1995	865,848	16,451	18,183	19,915
2000	886,759	16,468	18,202	19,935

PART II

PREDICTING CRIME FOR WASHINGTON STATE:

APPLICATION OF THE DIFFUSION MODEL AS AN AID FOR PREDICTING CRIME

PREDICTING CRIME FOR WASHINGTON STATE

The purpose of this study is to present a reasonable method of predicting the volume of crime in Washington State. As with most predictions and forecasts, this effort is at best conditional. In many cases the current methods are quite crude; unfortunately, using more complex methods does not automatically improve ones predictive accuracy. In other cases, some of the data requirements for prediction models exceed the data available to any individual state.

As a preliminary, this report will provide a review of the various methods that have been used to predict crime and then it will present an alternative method for predicting crime which is practical at the state level. This will include reviewing linear projection, multiple regression methods, log linear analysis, and finally, the application of a mathematical diffusion model.

Methods of Predicting Crime -- Early Efforts

Many crime forecasts are simple time series projections --i.e., linear projections-- of the past volume of crime. This method, although simple, is theoretically void. The assumption of linear projections is that contributing factors to crime are stable and will interact without change throughout time. Obviously, such assumptions have little to do with reality except in the very short run.

As inadequate as simple "straight line" projections are, there was little else known until recently that would be useful for predicting crime. Only within the past fifteen years has the size of the future population been recognized as a viable predictor of crime. This apparently simple idea still remains the most commonly used predictor. The relationship between crime and population is, however, considerably more complex than the simple idea that as the volume of the population increases the volume of crime also increases. More specifically, the age structure of the population is key to understanding the change in the crime volume patterns. Studies such as Christensen, (1967); Sagi and Wellford, (1968); Ferdinand (1970); and Wellford, (1973); make the argument that the relative size of the age group of males from 15 to 24 years of age is positively related to the variation in the crime rates and, therefore, the volume of crime. These studies, also, consistently conclude that change in the age structure alone can account for only a relatively modest portion of the change in gross crime rates and volume. Therefore, while age structure provides a valuable source for the explanation of crime, no claims are made that it is a final solution. At the same time, no other variables as useful as the age structure for explaining the rates and volume of crime have been isolated. As recently as 1972, researchers have reported that it is extremely difficult to derive crime rates from any base other than population (Schmid and Schmid, 1972).

Methods of Predicting Crime -- Recent Efforts

Recent efforts at explaining and predicting crime offer interesting new insights into the problem. The works chosen here for review are not all inclusive of the literature, but they do produce some of the latest and most sophisticated efforts. The works reviewed herein are Pullum, 1979; Klepinger et al., 1979; Fox, 1978; and Cohen et al., 1980. Generally, these works display three processes that are used for formulating prediction schemes. First, Pullum and the initial part of Klepinger et al. show how the relationship between predictor variables and arrest rates can be specified. Second, the second half of Klepinger et al. and Fox exhibit current thinking on multivariate analysis, and thirdly, Cohen et al. are included as an example for a sophisticated theoretical model.

Pullum (1978) initially and later, Klepinger et al. (1979), using logit analysis, show that the national arrest rates are not only dependent upon the age structure of a population but also are dependent upon period and cohort efforts. Not surprisingly, both of these studies reconfirm the importance of age structure for understanding criminal behavior; but, more important is the introduction of period and cohort effects. Period effects are best understood as unique historical events (in this case events within a single year) which impact the tendency to commit crimes and be arrested. Cohort effects are the unique events or situations which impact the criminality of a specific age group. One example of a cohort effect is the assumption that "baby boom" youths have experienced greater competition in all phases of life when compared with other, less crowded, cohorts.

The Pullum and Klepinger et al. analyses show that period and cohort concepts have significant impact on arrest rates. The birth cohorts from 1948 to 1958 (i.e., in 1980 people between the ages of 22 and 32) in the Pullum analysis and from 1948 - 1960 cohorts (or between 20 and 32 years of age) in the Klepinger et al. study show an increasing tendency for arrest for each successively younger cohort. However, Klepinger et al. go on to report that the 1960 - 1961 birth cohort has a decreased tendency for arrests. As encouraging as this down turn may appear, it must be realized that these younger cohorts have just entered or are about to enter their most active age span in terms of being arrested. In other words, the effect of life experiences on the generalized cohort effect will not really be known until these youths have passed through the critical age period of late teens and early twenties.

Next, these logit analyses show that there has been about a 60 percent increase in the period effects between 1964 and 1974. Then from 1974 to 1977 there was a decrease of 30 percent in the period effect. This pattern of period effects indicates that until 1974 the events within each successive year had a worsening effect leading to an increased arrest rate for persons of all ages. However, since 1974 the period effect suggests that the current events are related to a decrease in the arrest rate. It is important to note that the period effect is the only variable that has followed the recent trend of the leveling or reduction in the crime rate that the nation has experienced.

In summary, these logit analyses have found that age, cohort, and period effects are reasonably related to arrest volume. Futhermore, because it is possible to make theoretical arguments about the relationship between the changes of any of these parameters and the change in arrest volume, it might be supposed that these variables may be good predictors of future arrest patterns. Unfortunately, using these variables as predictive indicators assumes that we know how they will behave in the future. Population forecasts give us a rationale for using age structure as an indicator for future arrest and crime, but the cohort and period effects are not presently easily predictable and, are therefore, of limited use as crime predictors.

There is another way of predicting crime and arrest rates which is methodologically similar but statistically different from logit analysis. This method might best be called quasi-causal correlational analysis. Fox (1978) and the second part of Klepinger et al. (1979) provide good up to date examples of this approach. They selected variables that are statistically correlated to arrest and crime. Various attempts are then made to build a plausible explanation around these variables. A sample of some of the variables that are used in this type effort are: the number of police, the change in the number of police over time, change in the income of a populace over time, unemployment rates, and clearance rates.

Interestingly, Keplinger et al. use variables like those just listed as proxy varíables for the broader concepts of cohort and period effects. For example, they use the number of police in any given year as a means of representing period effects (i.e., those events within a single year which impact the propensity of the populace to commit crimes and be arrested). While it can be argued that the absolute number of police may impact the probability that the number of arrests made will change, it cannot be argued that the number of police adequately reflects the broader scope of events that impacts a populace's propensity to commit crimes and be arrested. Citing the weak theoretical underpinning of

Keplinger et al. -- and the same criticism can be made of Fox -- is not noted to malign the efforts of the authors, but to more accurately represent our current understanding of the criminal process.

Given the theoretical basis for the types of variables used by Klepinger et al. and Fox the method of explanation open to them relies on various combinations of weakly specified multiple regression models. Klepinger et al. use different variations of multiple regression models with the goal of increasing the percentage of the variance explained for the number of arrests. At this they are quite successful, obtaining R^2s (i.e., the percentage of variance explained) of 80% to 90%. For prediction purposes, the trends of these significant variables are extrapolated to give future arrest estimates. Fox uses a nonrecursive model, which mathematically is much more complex than the static model used by Keplinger et al. but which has the advantage of including feedback effects. Although both studies use similar independent variables, Klepinger et al. proposes to explain arrest volume and rates, while Fox proposes to explain crime and clearance rates.

At first glance, Fox's predictions appear quite different from Klepinger's et al. predicted arrest rates. Initially, it might be surmized, that because similar independent variables were used, the difference between the two studies may be due to the dissimilar dependent variables employed in each. To overcome this problem there may be a translation for Fox's data which provides at least a rough comparison. As just noted, Fox calculates estimates for both crime rates and clearance rates. Clearance rates for Fox are simply the percentage of reported crimes that are solved. Multiplying the percentage of crimes solved by the crime rate yields an outcome (clearance / 100,000) which is analogous to the arrest rate and should make the Fox and Klepinger et al. works roughly comparable. The reader should note that this procedure does not yield a true arrest rate (the number of reported arrests per 100,000 population). However, by assuming that each cleared crime yields one arrest (actually the ratio for cleared crimes to arrest is somewhat less than 1) we should get a biased, but generally comparable, set of data.

Following this procedure, Fox's predictions on what the arrest rate might be in the future does not agree with Klepinger et al. In general, it appears that Fox's nonrecursive model indicates that there will be a continual increase in the arrest rate until year 2000. On the other hand, Klepinger et al. predict a downturn in the arrest rates after the mid 1980's which would last until the year 2000 at which point an increase in the arrest rate would be expected.

Even though this comparison is extremely rough, one has to raise the question; "How can similar analyses lead to results that lead in different directions?" The key to this question probably lies in the varied use of the variable age structure. As had already been established, the age structure of a population is closely tied to the amount of crime that is committed and the number of arrests that are made. The problem becomes clearer when it is recognized that Fox severely limited the predictive power of his model because he used only blacks as his population variable. Fox's apparent thinking was that because blacks have a higher correlation with crime rates than whites; the number of blacks should be a better predictor. But he overlooks the fact that the vast majority of change in the crime rate is caused by the variation in the much larger combined population of whites and blacks and not the much smaller young black population. Therefore, Fox's predictions are based on the variation in a specific subpopulation which overestimates the change in the total population.

The important thing to notice about the multiple variate regression type models is that neither of these models -- and they are the most recent and comprehensive models presently available -- predict the leveling off of the crime rate or volume that we have experienced in the past four years. Fox's model generally predicts an ever increasing crime rate, while the Klepinger et al. model, which is influenced in a greater sense by variation in the population, does not see the arrest rate dipping until the mid 1980's.

The final method of predicting crime discussed in this report is more theoretical than those discussed earlier. Cohen, Felson, and Land (1980) present a method of predicting crime that is based on opportunity theory. The advantage of the opportunity theory for predicting crime patterns claimed by these authors is that their macro causal mechanism identifies measurable characteristics in society which are the causes of crime. In other words they claim that their theory taps the "real" determinants of crime while the other efforts of predicting crime -- specifically those like Fox and Klepinger et al. take advantage of variables that, perhaps by coincidence within specific time periods, are correlated to crime but are not necessarily determinates of crime. If their assertion about the validity of their variables is accurate, then their ability to predict crime patterns using opportunity theory should be a vast improvement.

The Cohen et al. opportunity theory includes such assumptions as: (1) criminal offenders prefer property targets that are located in sites with fewer, rather than more, potential guardians; (2) those individuals who do not have primary group ties are less likely to act as guardians for property (3) the decrease in the density of a population in

residential locations produces an increase in criminal opportunity; (4) an increase in the number of persons in transit produces an increase in criminal activity. A density index which is the number of households exposed to the risk of residential property crime because someone is not home divided by the number of households is used to represent the first, second, and third assumptions. The unemployment rate is used to represent the fourth assumption. The rationale for this is based on the idea that the higher the unemployment rate, the fewer people there are in transit and, therefore, the opportunity for car theft and other property is reduced. It is also believed that higher unemployment is related to more secure residences. Total consumer expenditures in year t-2 (i.e., two years prior) for durable goods other than automobiles are used as a measure of non-automobile targets. Next, the proportion of the U.S. population aged 15 to 24 in each year is used as the only offender related variable (note this is the age structure variable that was discussed earlier). Finally, in each crime model the lagged crime rate is introduced to determine if the speed at which the exogenous variables (those variables listed above) take effect on the specific crime rate. If the coefficient for this variable tends to zero, then the effects of exogenous variables are supposed to be spontaneous. And if the absolute value of this variable is greater than zero, then the effects of the exongenous variables would be viewed as having a distributed effect over time (see Land, 1979 for a discussion of this point).

Using various combinations of the variables listed above the Cohen et al. models were able to explain a very large percentage of the variance (98% to 99%) for each type of property crime rate. Then in order to test the forecasting capabilities of the opportunity theory model, the authors used crime rates for 1973 to 1977 as a test of the models coefficients developed using the 1947 to 1972 data. This ex-post forecasting analysis showed that the projections from the coefficients generated from 1947 to 1972 data were within statistical limits of confidence relative to the actual crime rates. However, the fit between the historical trends and the actual 1973-1977 crime rates showed a disconcerting pattern. The fit between these two sets of data indicated an over estimation of the crime rates. But most disconcertingly, the deviation between the actual and the projected crime rates increases over time.

Next, Cohen et al. provide an <u>ex-ante</u> forecast using their opportunity theory model. A forecast is <u>ex-ante</u> when it retains the variables in the model but uses projections of these variables as the basis for estimating crime rates rather than the known values themselves. Using such a method, the authors with some minor adjustments, were able to forecast that the crime rate on a national level will decrease between 16 and 33 percent by 1985. The Cohen et al. study provides predictions similar to Klepinger et al. but, as with the other studies, the Cohen et al. analysis has not been able to explain the deceleration of the crime rate after 1974.

Conclusionary Statements About Current Literature on Crime Prediction

As the review of the various attempts to predict crime attest, the forecasting of crime, as well as any other social phenomena is, at best, a conditional undertaking. All of the above mentioned methods of explanation and forecasting have a common logic. First, an attempt to develop a theory of the relationship between crime and casual factors of crime is conducted. This can range from the theories with weak underpinning like Fox and Klepinger et al. to a more organized effort like Cohen et al. Second, the relationship between the variables that cause crime are then arranged in some sort of mathematical model. These models, range from the simple to the complex. A simple model, based on the age structure of a population, might consist of a process where various weights are attributed to different age groups. As the structure of the population changed over time, the volume of crime would be expected to change. Even though this method is simple and ignores the importance of other variables, it is a process that few could disagree with except for its incompleteness. The Cohen et al. study is a good example of a more complex arrangement of variables. For example, they examine the statistical and substantive utility of various multivariate models by comparing the efficacy of additive and multiplicative models and by allowing for the dynamic effects of the independent variables.

The third general step, once it has been decided that the model is sufficiently representative of social reality, is to apply the model in a forecasting sense. Based upon the very large percentage of the variance that has been statistically explained by Fox, Klepinger, et al., and Cohen et al., it might be believed that any one of the models would be a good predictor of crime. This would be the case if the model represented the underlying structure of the forces that lead to crime. But as Cohen et al. recognize, the process of model building and forecasting is only truly correct if the variation in the factors in the model represent the true structure of the societal forces that lead to crime. And on this account all of these recent studies have failed. In a limited time span they explain an exceptional percentage of the variance in the crime pattern, but when used in forecasting they all fail to predict the downturn of crime experienced in the mid 1970`s.

It is a little unfair to hold the crime forecasting efforts of these authors to the stringent test of predicting future criminal behavior of American society. Compared to what was known in 1972 (Schmid and Schmid), all of these efforts are examples of progress in methodology. However, the limitations of the above studies need to be recognized as well. As Cohen et al. indicated, the work of Fox has very weak theoretical underpinning. And because of the similarity of Klepinger et al. work to Fox, criticism can be generalized to the Klepinger et al. work.

In spite of the noted weaknesses, it is interesting to note that even though Klepinger et al. and Fox use similar predicting variables, their conclusions, as was noted earlier, are quite different. Even the Cohen et al. article which is theoretically advanced, shows a distressing progressive tendency to over estimate the national crime rate. This may be the case because for all variables except for the change in the age structure, all of the other variables in the Cohen et al. and for that matter the Fox and Klepinger et al. efforts, are on a generally increasing monotonic trend. And disillusioning as it might be, it is possible that most of the variables discussed and tested in these efforts may be coincidentally related to the monotonic increase in crime. Then again, it is just as likely that some of these variables might, in fact, be determinants of the crime rate, but that their importance in the "real" model has lessened. Irrespective of these considerations, the fact that the crime rate and crime volume have dropped without apparent explanation within the past few years is problematic. Further, it is a problem that the works discussed herein have not addressed.

Rationale For Washington State Crime Predictions

Returning to the question at hand, the answer to how the forecast of crime for Washington State might be addressed remains a problem. The only factors that one can be certain fit crime patterns are the age structure of the population, period effects, and cohort effects (Pullum, 1978). Unfortunately, the only one of these for which we have sufficient evidence for what the future might be is the age structure. As was discussed earlier, the future pattern of cohort effects (the differential life experiences of each specific birth cohort) are uncertain, and the period effects (the differential life experiences of the total population within one year), even though important, are conceptually unspecified. Moreover, even if we wanted to use some of the same correlate variables as Fox and Klepinger et al. or the opportunity theory variables of Cohen et al., it would be found that Washington State has not maintained time series data on many of these variables. Futhermore, all of the forecasting attempts described above have used national crime or arrest data. The advantage of this data is that the volume of the aggregated data far exceeds volume for Washington State. Therefore, the national data is less likely to be subject to variations introduced by local conditions. In statistical terms this is important because the national data will exhibit greater stability and less fluctuation than any single state`s data.

Given these problems, the question has to be raised as to whether or not it is possible to make a reasonable crime forecast for the state of Washington. In part the answer must be no. Washington State, as most states, will have a more difficult time trying to project crime patterns than will the national efforts. However, the battle is not lost. It is possible to use age structure as an important predicting variable. As has been noted earlier, the relationship between crime, and most specifically arrests, is strongly correlated with those males in their late teens and early adulthood.

However, simple logic conflicts with the desirability of performing a crime forecast using only variation in the age structure (i.e., the "at-risk group" of potential offenders). Such a simple design assumes that the rate of offending remains stable throughout time, an assumption that is blantantly contradicted by known variations in the crime rate. But unfortunately, a satisfactory explanation of the change in the crime rate has not been forthcoming. Even opportunity theory fails to track the recent decline in the crime rate. Therefore, if an alternative projection of the crime rate could be achieved, then a major step would be made toward a more reasonable forecast.

Fortunately, an alternative method of explaining the variation in the crime rate can be found in the social diffusion model. Diffusion models were adapted from the physical sciences for the social sciences by Dodd (1955) and Coleman (1959). In the most general sense, diffusion models are based on the concept that there are basic forces that contribute to the adoption of a social behavior among a population. When a new behavior appears in the population and social forces are activated, the behavior begins to be adopted throughout the population. The spread of the behavior thoughout a population may be partial or total.

Applications of the diffusion type models to crime forecasting are first observed in recent efforts by Snow and LaSante (1980). However this application uses a physical science model which obscures the social nature of the problem. MacCorquodale and Pullum's (1974) recent study provides an application of diffusion models which is more pertinent because it is applied to a social situation. These authors' study applies the diffusion model to the evaluation of women's acceptance of birth control practices. Using the MacCorquodale and Pullum social diffusion study as a guide, the application of this procedure can be generalized to crime rates.

As the diffusion model is used in this application, there are two underlying assumptions which represent the driving social forces. The first assumption posits an external force and the second assumption posits an internal force. The first assumption posits that forces outside of the adopting group operate at a constant level until all of those who are going to adopt a new behavior eventually do adopt it. In other words, the change of adoption of the behavior in question has no bearing on the number of people who have or have not adopted the behavior at any time during the process. An example of such external force would be the adoption of a new product which is influenced solely by a marketing effort. In the case of crime rates, the outside force is possibly represented by the change in social stability. As a society becomes more unstable (e.g., the legitimacy of the system is questioned or there is great social change), the propensity of a population to commit crime also increases. As indicated in Figure 1, the graph of the external social force is represented as a constant in the model and the probability of any one person adopting the behavior throughout the life of the diffusion process is also constant.

Mathematically, the first assumption is represented as $Y = w_1(N - X)$. Where Y equals the number of persons who adopt criminal behavior between any time period t and t +1; N equals the number of possible adopters; X equals the number of accumulated adopters among N; and w_1 is the expected rate of constant change.

Figure 1: Characteristics of the "External" Force

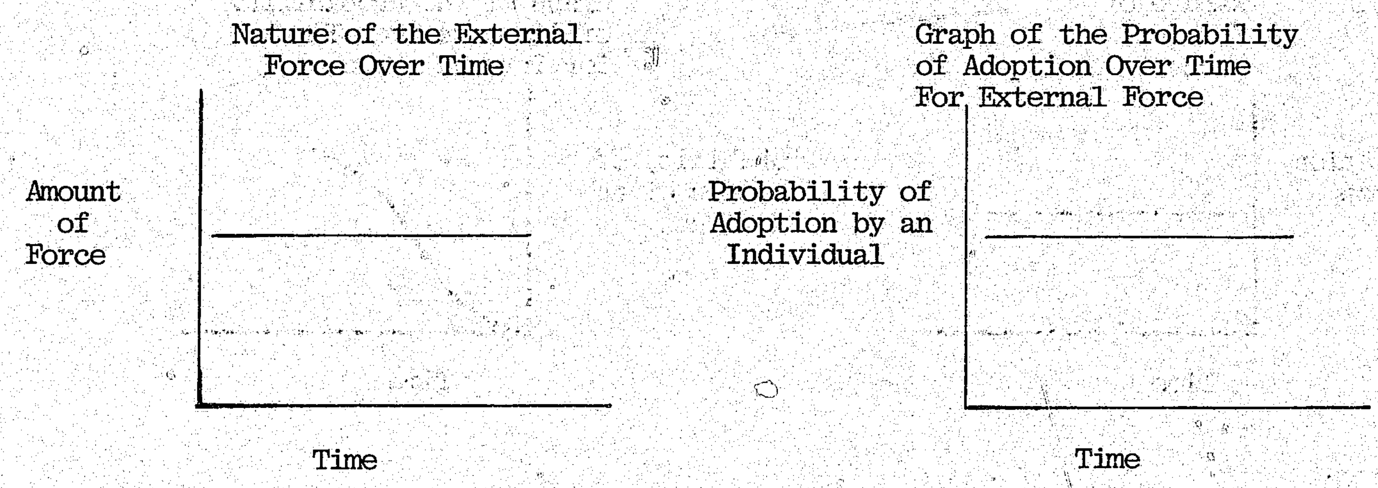
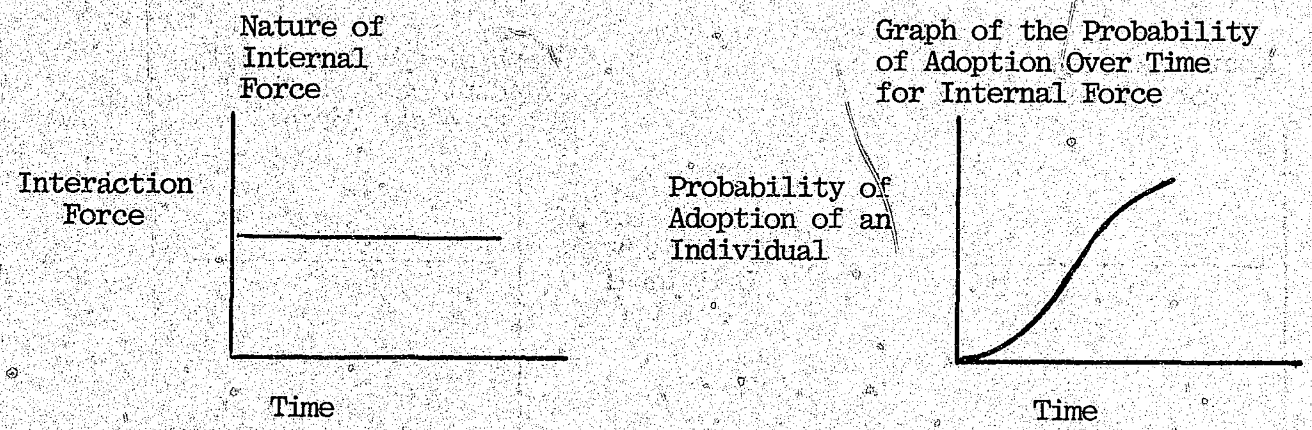


Figure 2: Characteristics of "Internal" Force



The second assumption of the diffusion model used in this analysis is the idea that adoption of a behavior is proportional to the fraction of the population that has accepted it at time t. As the proportion of acceptors increases, a nonacceptor is increasingly likely to encounter acceptors in daily interaction. Put simply a force that causes behaviors to be adopted in a given population is the interaction of individuals within that population. This force of diffusion is best called the interaction effect. Graphically, the nature of interaction and the probability of adoption as shown in Figure 2.

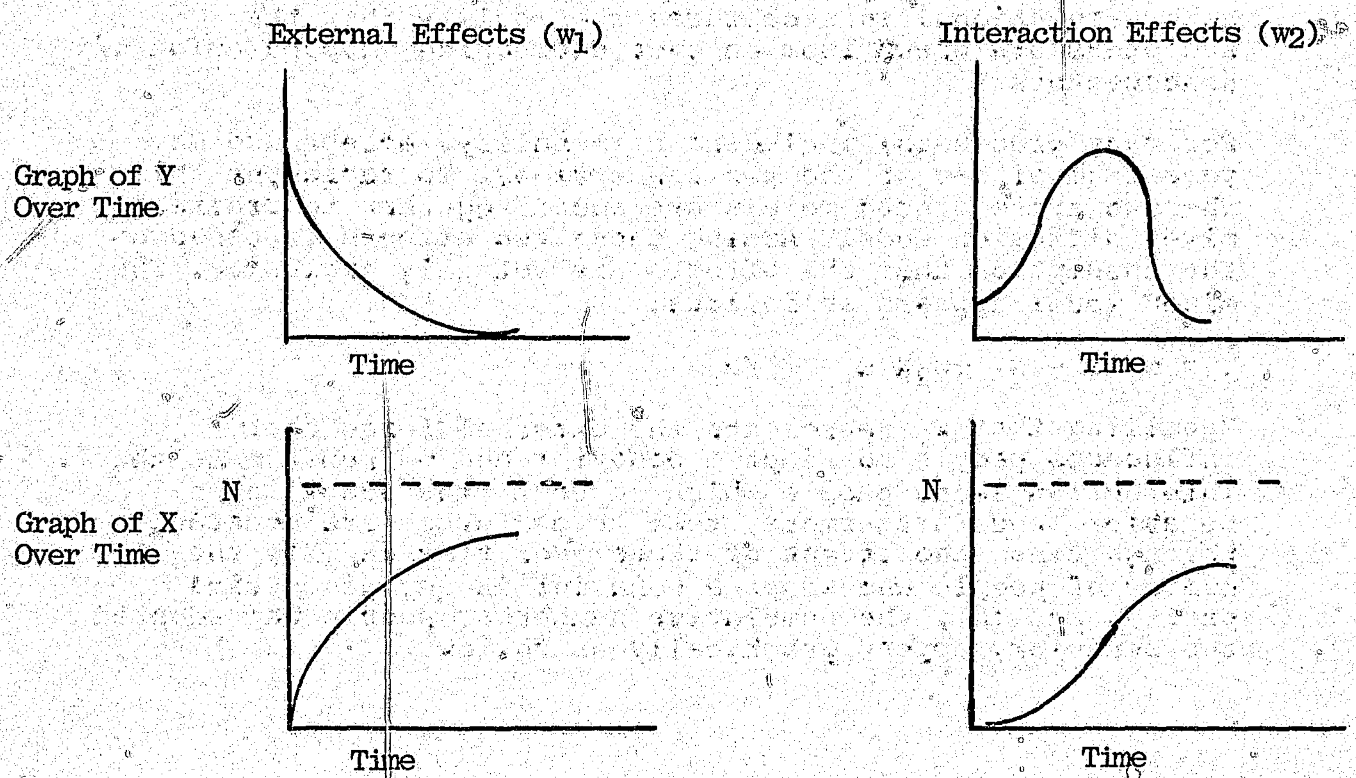
Mathematically, this assumption is represented as $Y = w_2X(N-X)/N$. Notice that the potential population that can be treated as potential acceptors is formalized as N - X in both assumptions. This captures the reality that the acceptors are drawn from an ever decreasing subpopulation of nonacceptors.

For many processes, including criminality, acceptance may come from either of the two assumptions. To represent this, the two above stated models are added together to create a mixed diffusion model. Adding these two effects is based on the assumption that the effects are mutually exclusive. The mixed model appears as follows:

$$Y = w_1(N - X) + w_2X(N - X)/N$$

Recalling that w_1 represents the external force that influences people to adopt a behavior and w_2 represents the interaction among people which leads to the adoption of behavior, and furthermore, that these forces are constant through time, the effect of these over time on (Y), the number of people who adopt a behavior in any given time period, and (X), the cumulative number of people who adopted the behavior, appear graphically as follows:

Figure 3: The Characteristic Effects of External and Internal Forces on (y) the Number of People Who Adopt Any Time Period and (X) the Cumulative Number of People Who Adopt Over Time



"N" equals the Total Size of the Target Population

Combining the affect of w_1 and w_2 for the accumulation of the adoption of the behavior over time (X), it is obvious that the mixed diffusion model predicts that once a force outside a population begins to exert its influence then there may be different periods of acceleration depending on the values of w_1 and w_2 but, that, eventually the adoption of a behavior will reach a limit and, as it does so, the rate and the increase in the total number of adopters will slow down.

By its nature, the mixed diffusion model is different from the other methods of predicting the crime rates discussed earlier. Where the methods discussed earlier focus on a specific set of prediction variables as a means of estimating a future phenomena, the diffusion model focuses on the social process of two variables -- outside influence and social interactive influence. In this case, the socially disorganizing events of the late 1960's and the early 1970's, according to the diffusion model, will eventually run their course culminating in a new equilibrium. Each period of social change, be it an aggravating change or an ameliorative change (i.e., the curves can either increase or decrease), can be followed by a period of relative stability; or because of new events, enter into a new epoch and a new period of diffusion of behavior. Another thing to recognize about the diffusion of behavior is that given any size of an eligible population, the model does not require that all or even a majority of the population adopt the behavior. Therefore, a poorly diffused behavior would be represented by a relatively flat curve while a more successful diffusion would be represented by a much steeper curve.

In addition to quantification of the parameters representing the external force (in this case the societal conditions) and the spread of behavior caused by the interactive qualities of a group, another important characteristic of the mixed diffusion model is that it is possible to determine the fit between the actual changes in crime rate and the curve generated by the best fit to these rates. Starting with the mixed diffusion model equation, it can algebraically translate into a form amenable to multiple regression analysis from whence a fit of the data to the diffusion curve can be determined. Here where Y represent the fitted values of Y, the model appears as follows:

Mixed Diffusion Model

$$Y = w_1(N - X) + w_2X (N - X)/N$$
$$= (N - X) \quad (w_1+w_2X/N)$$
$$= w_1N - w_1X + w_2X - w_2X^2/N$$
$$= w_1N + [(w_2 - w_1)X] - w_2X^2/N$$

or in a multiple regression form:

$$Y = b_0+b_1X + b_2X^2$$

where

$b_0 = w_1N$

$b_1 = w_2 - w_1$

$b_2 = - w_2/N$

Application of the Mixed Diffusion Model to Washington State Reported Crime

One of the important reasons for using the mixed diffusion model as a method of making crime projections for Washington State is that the diffusion model follows the leveling off of the crime rate since 1976 more closely than the other methods. Futhermore, the diffusion model provides a rationale for the leveling off of the crime rate after such a long period of increases, (i.e., the growth is approaching its asymptote). Because of this new information the actual projection of crime volume is greatly simplified. Once it is determined what a reasonable projection of the crime rate might be, (here it is predicted that it remains relatively constant for the immediate future) one merely needs to multiply the estimated at-risk group by the expected crime rates.

Population data for this analysis was obtained from the October 1979 State Population Forecasts by Age and Sex. Males 15 - 34 years of age are used as the "at-risk" group. This age group appears to represent that portion of the population in Washington State which is responsible for the majority of crimes (See Appendix 1).

The crime data for Washington State was drawn from Uniform Crime Reports for the respective years. Because the F.B.I. changed the method of recording larceny in 1972, a correction is necessary to enable the simultaneous use of pre-1972 and post-1972 data. The procedure to make corrections for the change in larceny reporting in 1972 by the F.B.I. can be reviewed in Appendix 2.

These data were then used to calculate the diffusion models for estimating crime rates. The original calculations were done using the raw change in the annual crime rate (which is Y where Y equals the change in the crime rate between t and t +1). A perfect fit of the diffusion model would require that the crime rate for the at-risk group would increase each year until the crime rate approached its asymptote at which point the annual change in the crime rate would be expected to level off and eventually decrease.

Using the raw annual changes in the crime rates for "total reported crime," "property crime," and "violent crime" the diffusion model does not show a good fit. As Table 1 shows the variance explained is quite low and significance levels are poor. However, Table 1 also shows that the mixed diffusion model, which is a combined linear and parabolic model, has a better fit than either the isolated linear or parabolic model. The relatively poor fit of the mixed diffusion model is not so discouraging when the raw data is examined (see Figure 4 -- violent crime example). The variability in the annual change in raw data obviously impedes the fitting of any curve. In the light of the vacillation of the raw data, data smoothing seems to be a reasonable approach as a method for attempting to improve the fit.

Two major techniques were used to smooth the data. First, the economically depressed years 1970 - 1973 in Washington State were adjusted to better reflect the national trend in incresing crime rates. To keep the adjustment meaningful to Washington State, the linear trend of the years 1961 to 1969 was used to predict what the increase in the annual crime rate might have been without the severe economic impact. Following the re-estimation of the change in crime rates, a three year moving average was used as the second method of smoothing the data. As Table 2 and Figure 5 indicate, the smoothed data for total crime provides a much more reasonable fit for the mixed diffusion model.

Table 1: Comparison of Linear, Mixed Diffusion Model and Parabola Fits for Total, Violent, and Property. Change in Crime Rates 1961-1978: Raw Data

	MODEL	SIGNIFICANCE	b FOR X	b FOR X^2
	Linear	.960	.003	
TOTAL CRIME	Mixed Model	.574	.588	-1.287
	Parabola	.949		-.008
	Linear	.540	.031	
VIOLENT CRIME	Mixed Model	.320	.407	-14.212
	Parabola	.725		.670
	Linear	.930	.005	
PROPERTY CRIME	Mixed Model	.574	.628	-1.450
	Parabola	.982		-.003

Table 2: Comparison of Linear, Mixed Diffusion Model and Parabola Fits for Change in Total Crime Rates 1961-1978: Smoothed Data

	MODEL	SIGNIFICANCE	b for X	b for X^2
Total Crime	Linear	.522	. 02	
	Mixed Model	.001	.619	-.845
	Parabola	.877		.007

Figure 4: Change in Violent Crime Rate between t and t + 1

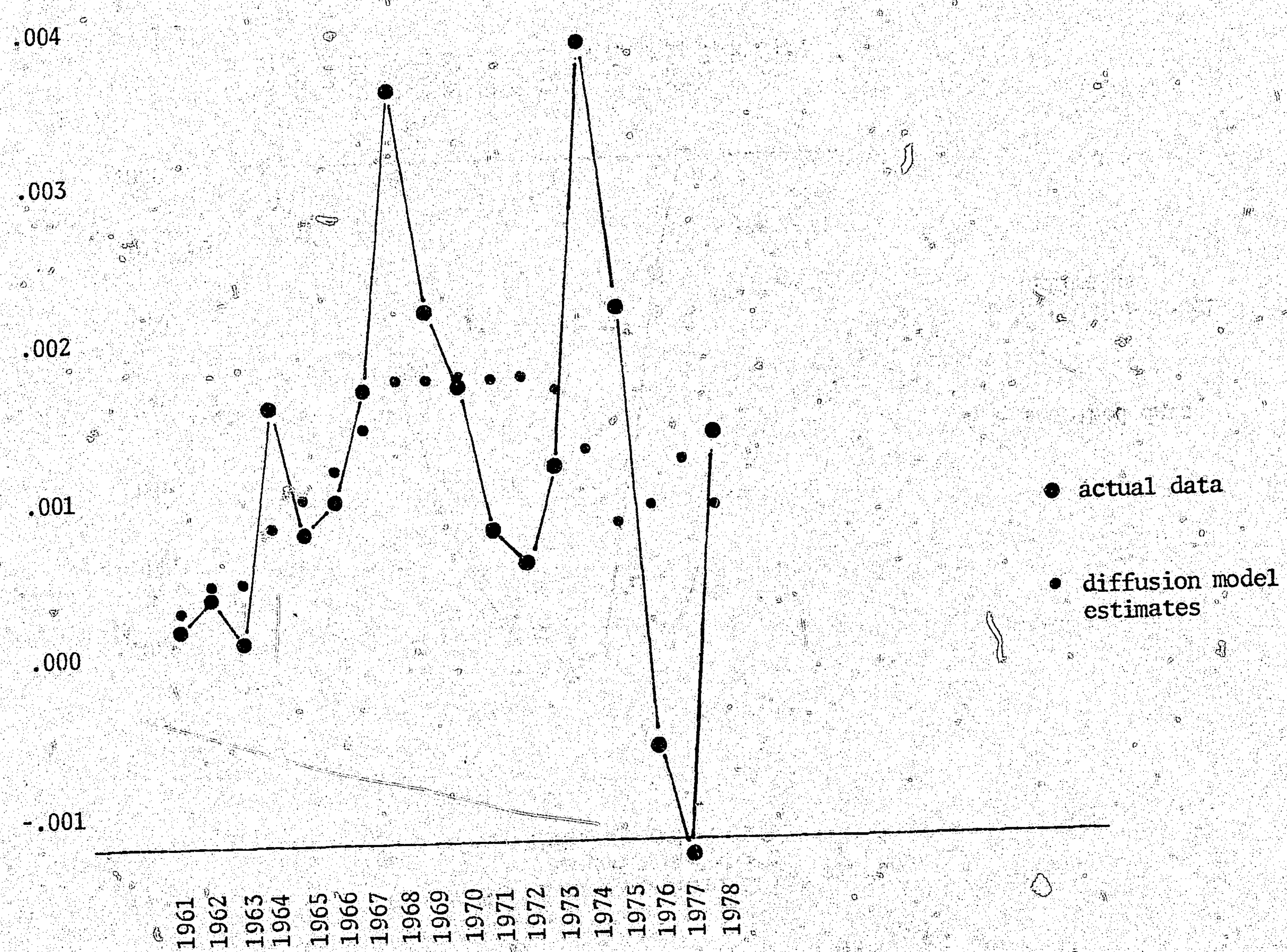
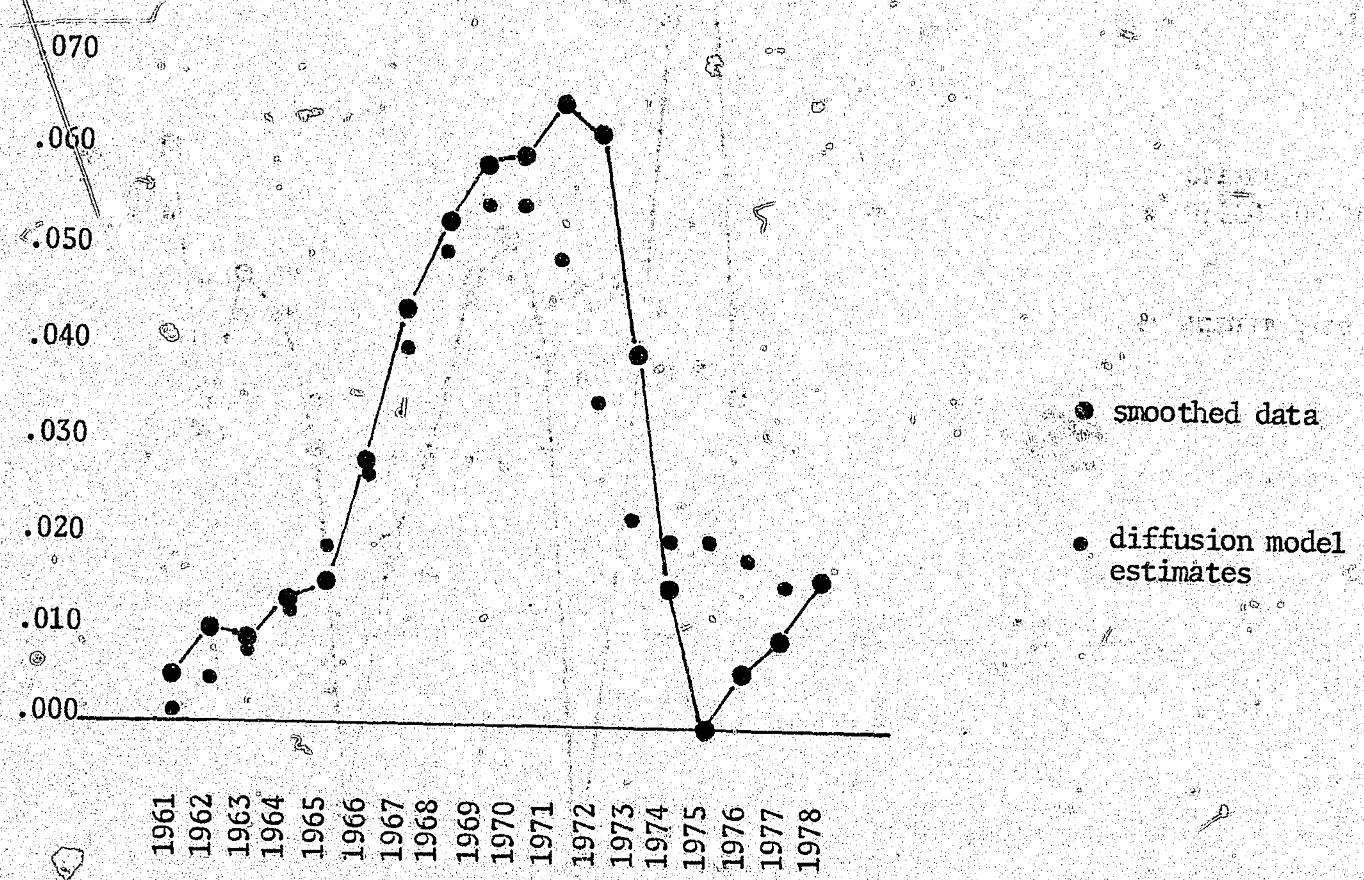


Figure 5: Change in Total Crime Rate between t and t + 1 Using Smoothed Data



Interpretation and Crime Prediction

Comparing the results of the mixed diffusion model to the previously discussed literature, the main advantage of the mixed diffusion model is that it mathematically follows and theoretically predicts the leveling off of the crime rate in Washington State, and one could conjecture, the nation. On the other hand, the other methods of crime prediction failed to explain this leveling off of the crime rate. Therefore, even though these other models explain a remarkable percentage of variance, the mixed diffusion model appears to be a reasonable method of estimating the rate of crime. As was noted earlier, once the asymptote of the diffusion curve is reached, it then predicted that the rate of crime for the at-risk group will remain constant or decrease somewhat. For the state of Washington this appears to be the case (Table 3). In fact it appears that in the last couple of years, the change in the rate of crime has stabilized.

However, as the 1978 increase in the crime rate indicates, even if the crime rate has stabilized, we can still expect a wide degree of variation from year to year. However, the diffusion model would have us predict that on the average the crime rate would remain relatively stable. A major shortcoming of the diffusion model is that it is limited to predictions within one episode or period of change. Once the asympote is reached one must look to emerging external forces of change which will lead to a new period of diffusion. As history has shown, a new epoch of change can be either in the positive or negative direction.

The final conclusion for immediate crime prediction in this state is that crime rates have, for the present and for the near future, stabilized. However, as the latest population reports indicate, due to the large immigration into Washington State, the at-risk population will continue to increase. Therefore, with even a stabilized crime rate, the volume of population in the state of Washingon will increase enough so that the volume of crime will continue to increase.

TABLE 3: CRIME RATES* FOR WASHINGTON STATE
1961 - 1978

YEAR	TOTAL CRIME RATES	VIOLENT CRIME RATES	PROPERTY CRIME RATES
1961	.110	.0043	.107
1962	.117	.0047	.112
1963	.121	.0048	.116
1964	.141	.0064	.134
1965	.138	.0072	.131
1966	.154	.0082	.145
1967	.181	.0099	.171
1968	.222	.0135	.209
1969	.285	.0157	.269
1970	.296	.0140	.282
1971	.292	.0148	.277
1972	.292	.0154	.277
1973	.304	.0162	.287
1974	.349	.0201	.329
1975	.350	.0223	.328
1976	.324	.0217	.302
1977	.312	.0204	.292
1978	.329	.0218	.308

*CRIME RATES ARE FOR THE AT-RISK GROUP OF MALES 15-34

CRIME RATE IS CALCULATED AS FOLLOWS: NUMBER OF CRIME/NUMBER OF MALES 15-34

APPENDIX 1

DATA JUSTIFYING THE "AT-RISK" GROUP

CORRELATION MATRIX FOR DIFFERENT AGE COHORTS AND SELECTED CRIME CATEGORIES (1965--1976)

Age Cohorts	Total Reported Crime	Property Crime	Burglary	Person to Person Crime	Assault
Total State Population	.95	.92	.95	.94	.85
Total Male Population	.92	.90	.93	.92	.82
Males 13--14	.54	.36	.60	.55	.23
15--19	.97	.92	.97	.97	.88
20--24	.95	.93	.95	.95	.86
25--29	.97	.98	.95	.96	.96
30--34	.96	.98	.89	.92	.96
35--39	.17	.38	.14	.17	.36
40--59	.20	.36	.54	.48	.20
Males 15--34	.98	.97	.96	.97	.93

APPENDIX 2

ESTIMATING THE NUMBER OF REPORTED LARCENIES IN WASHINGTON STATE 1961 - 1972

Appendix 2

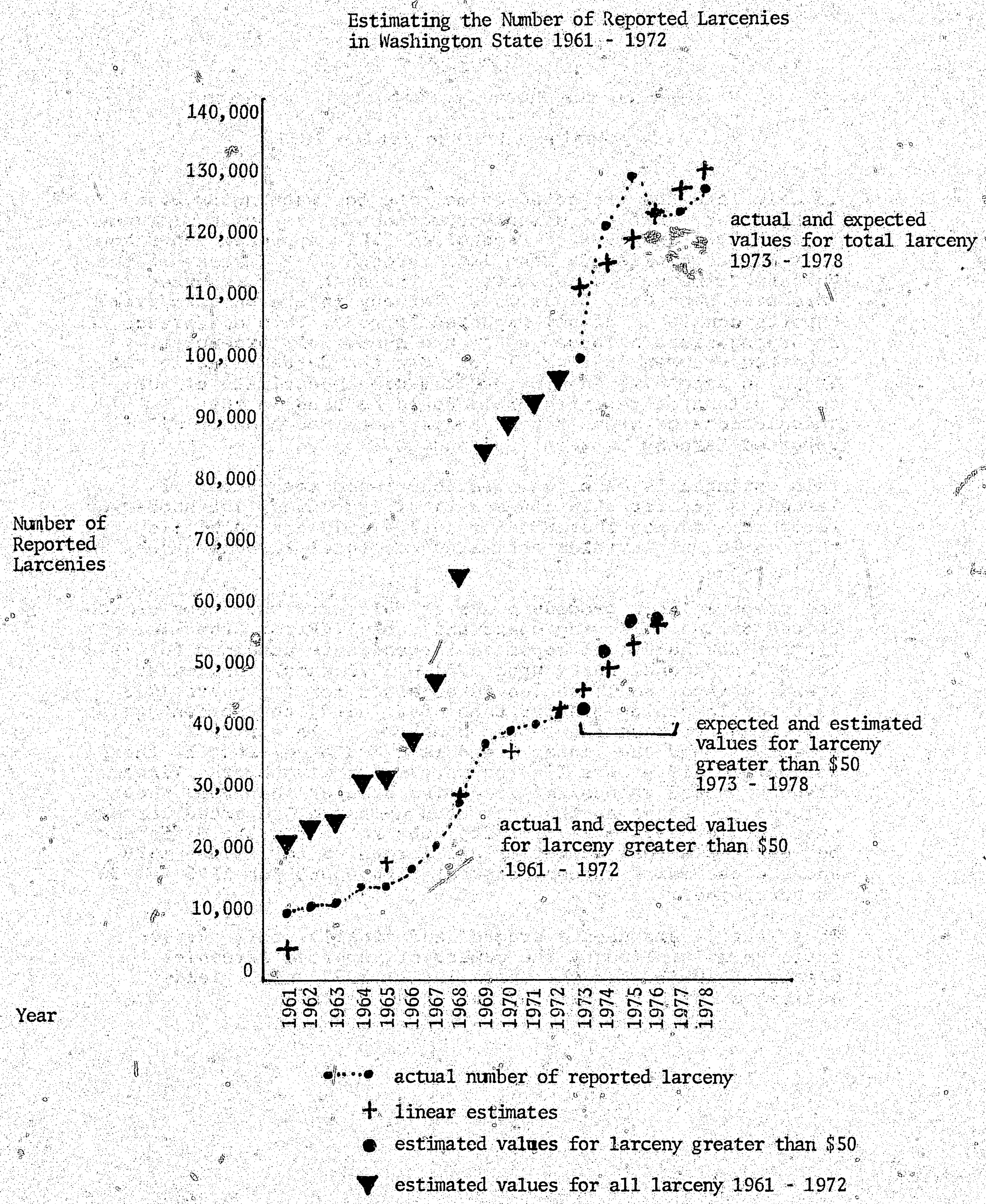
Estimating the Number of Reported Larcenies in Washington State 1961 - 1972

To calculate the projected crime rate for Washington State it is necessary that the different methods of reporting larceny between 1961 and 1978 be reconciled. This appendix shows how this was accomplished. From 1961 through 1972 larceny in the Uniform Crime Report consisted of the number of reported larcenies over $50. Since 1972, larceny in the Uniform Crime Reports consisted of all reported larceny. This difference in reporting cause a large gap in the number of larcencies reported between 1972 and 1973. (See the dotted line in the graph on page 47.) In order that a single estimate of the total volume of reported crime could be used in the calculations of crime rates, an estimate was made of all reported larceny between 1961 and 1972.

This estimate is based on a ratio between the number of larcenies greater than $50 and total larcenies. The number of larcenies greater that $50 for 1961 - 1972 are multiplied by this ratio which yields estimates for total larcenies for 1961 - 1972.

The steps in this procedure are as follows: (the steps can be traced on the following chart and table). First, the linear fit for the number of reported larcenies is obtained for 1973 to 1978. Second, based upon 1961 - 1972 data, the linear trend of reported larcenies is obtained for the years 1973 - 1976 for larcenies greater than $50. Third, the percentage of difference between the reported number of larcenies from the linear fit and the linear trend is calculated. Fourth, these percentage difference figures were multiplied by the linear trend expected values for larcenies greater than $50. These values then serve as the estimated number of reported larceny over $50 for 1973 - 1976. Fifth, the ratio for the difference between the actual number of all larcenies for 1973 - 1976 and the estimated larcenies greater than $50 for 1973 - 1976 is determined.

These ratios are then averaged, and finally, this average ratio is multiplied by the number of reported larcenies greater than $50 for the years 1961 - 1972 which yields estimates for total larceny for these years.



Estimating the Number of Reported Larcenies
in Washington State 1961 - 1972
Number of Reported Larcenies
140,000
130,000
120,000
110,000
100,000
90,000
80,000
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
Year
1961
1962
1963
1964
1965
1966
1967
1968
1969
1970
1971
1972
1973
1974
1975
1976
1977
1978
actual and expected values for total larceny 1973 - 1978
expected and estimated values for larceny greater than $50 1973 - 1978
actual and expected values for larceny greater than $50 1961 - 1972
actual number of reported larceny
linear estimates
estimated values for larceny greater than $50
estimated values for all larceny 1961 - 1972

PROCEDURES FOR ESTIMATING THE NUMBER OF REPORTED LARCENY IN WASHINGTON STATE 1961-1972

	(1) NUMBER OF REPORTED LARCENY	(2) EXPECTED LINEAR TREND VALUES (BASED ON 1973-1978 ACTUAL DATA)	(3) EXPECTED LINEAR TREND VALUES FOR LARCENY GREATER THAN $50 1973-1976 (BASED ON 1961-1972 ACTUAL DATA)	(4) ESTIMATED VALUES FOR LARCENY GREATER THAN $50 BASED ON PERCENTAGE DIFFERANCE BETWEEN THE ACTUAL & THE EXPECTED VALUES 1973 - 1978	(5) DIFFERENCE RATIO BETWEEN (4) & ACTUAL NO. OF LARCENIES 1973-1976 (1)	(6) ESTIMATED ALL LARCENY 1961-1972 BASED ON DIFFERENCE RATIO & ACTUAL LARCENY $50 AND GREATER
1961	9,215					21,434
1962	10,197					23,718
1963	10,513					24,453
1964	13,510					31,424
1965	13,689					31,840
1966	16,263					37,827
1967	20,076					46,696
1968	27,640					64,290
1969	36,207					84,217
1970	38,488					89,523
1971	39,726					92,402
1972	41,232					95,905
***CHANGE IN REPORTING PROCEDURE						
1973	99,522	110,516	45,174	40,656	2.447	
1974	121,132	114,642	48,577	51,297	2.361	
1975	129,060	118,768	51,978	56,448	2.286	
1976	123,324	122,894	55,380	55,380	2.226	
1977	123,894	127,020			Average Difference ratio equals 2.33	
1978	127,954	131,146				

APPENDIX 3

DATA FOR DIFFUSION MODEL

DATA FOR DIFFUSION MODELS

YEAR	AT-RISK POPULATION	TOTAL NUMBER OF REPORTED CRIMES	NUMBER OF REPORTED VIOLENT CRIMES	NUMBER OF REPORTED PROPERTY CRIMES	(Y) CHANGE IN TOTAL CRIME RATE + TO ++1	(X) CUMULATIVE TOTAL CRIME RATE	(Y) CHANGE IN VIOLENT CRIME RATE + TO ++1	(X) CUMULATIVE VIOLENT CRIME RATE	(Y) CHANGE IN PROPERTY CRIME RATE + TO ++1	(X) CUMULATIVE PROPERTY CRIME RATE
1961	375,400	41,666	1,617	40,049	.003	.110	.0002	.0043	.002	.107
1962	390,000	45,561	1,817	43,754	.007	.117	.0004	.0047	.005	.112
1963	397,800	47,938	1,924	46,014	.004	.121	.0001	.0048	.004	.116
1964	409,600	57,641	2,622	55,019	.020	.141	.0016	.0064	.018	.134
1965	427,700	58,917	3,081	55,836	-.003	.138	.0008	.0072	-.003	.131
1966	447,000	68,621	3,663	64,958	.016	.154	.0010	.0082	.014	.145
1967	479,700	86,684	4,754	81,930	.027	.181	.0017	.0099	.026	.171
1968	514,400	114,392	6,970	107,422	.041	.222	.0036	.0135	.038	.209
1969	525,500	149,517	8,243	141,274	.063	.285	.0022	.0157	.060	.269
1970	536,600	158,648	7,546	151,102	.011	.296	.0017	.0140	.013	.282
1971	549,782	160,469	8,155	152,314	-.004	.292	.0008	.0148	-.005	.277
1972	559,750	163,501	8,627	154,874	.000	.292	.0006	.0154	.000	.277
1973	574,834	174,534	9,309	165,225	.012	.304	.0012	.0162	.010	.287
1974	598,384	208,875	12,036	196,839	.045	.349	.0039	.0201	.042	.329
1975	621,198	217,634	13,851	203,783	.001	.350	.0022	.0223	-.001	.328
1976	646,447	209,280	14,036	195,244	-.026	.324	-.0006	.0217	-.026	.302
1977	670,953	209,521	13,714	195,807	-.012	.312	-.0013	.0204	-.010	.292
1978	700,534	230,802	15,296	215,506	.017	.329	.0014	.0218	.016	.308

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