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Youth, Crime, and Deterrence: What Matters?

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Abstract

Both the press and professional criminal justice literature have speculated over reasons for recent declines in crime rates reported first in the Federal Bureau of Investigation's Uniform Crime Reports and subsequently in the Bureau of Justice Statistic's National Crime Survey. While some officials have claimed that these declines resulted from recent "get tough on crime" policies, equally vocal observers have pinpointed declining youth populations as the primary reason for the crime trends experienced.

This paper reports on the results of some exploratory analyses of these competing assertions. Three aspects of the relationships between youth, crime and punishment were investigated. A time-series model of crime rates, punishment risk, and size of the youth population was estimated using standard econometric methods. Alternative specifications of model form and punishment risk consistently supported the view that changes in punishment risks rather than changes in the size of the youth population accounted for changes in crime trends. An analysis of victim responses in the National Crime Survey adjusted estimates of the numbers of crimes committed by various age groups to account for the possibility that youth gang participation distorted perceptions of the prevalence of youth in criminal activity. It found that youths were indeed the most criminally active even after adjustment for group crimes. This analysis suggested that age composition must play some role in crime trends. A simple age composition model was developed to project crime trends based on age factors alone. After fixing the crime incidence rate for each age group at 1983 rates, the model forecast crimes for various points in the 1960 to 1983 period. The forecasts diverged rapidly from actual crime counts, suggesting that age trends alone are inadequate predictors of crime trends.

Introduction

Much of the speculation over the reasons for recent declines in crime rates involves the proposition that the United States is enjoying the benefits of changing demographics. The most significant change in the eyes of criminal justice professionals is that the U.S. population is growing older. American youths -- presumably a major crime-prone group -- are declining in representation in the overall population. Thus we should expect to see a decline in crimes per capita even if criminal justice policies on arrest and punishment remain constant.

To be sure, youths have declined as a percentage of total population. Persons aged 15 - 24 comprised 13.6 percent of the population in 1960. They peaked at 19.3 percent in 1977 and have declined ever since to 17.5 percent in 1983 according to the Bureau of the Census. Chances of being victimized by a serious crime were 1.88 percent in 1960, as measured by the FBI's Uniform Crime Report (UCR) Index. This risk climbed to 5.93 percent in 1980 and has since declined to 5.16 percent in 1983. The implications of these simple trends are buttressed by findings that youths are the most frequently arrested among age groups to present an attractive argument that demographics are an important factor in explaining or predicting crime trends.

But demographics need not be the only explanation. We find, for instance, that youths represented 17.5 percent of the population in 1969 as well as in 1983. Yet the chance of being a victim of a serious crime in 1969 were only 3.66 percent, versus 5.16 percent 14 years later.

One can advance a number of reasons for why these differences exist. Perhaps crime reporting to the FBI changed significantly over the period; perhaps other socioeconomic trends also contributed to the crime rates of the past two decades; or perhaps fluctuating criminal justice policies have operated to deter or encourage the commission of crimes, accelerating or retarding the influence of demographic trends. Possibly all three hypotheses are true. However, only the last hypothesis is investigated in this paper.

This paper presents findings from three analyses of the effects of age composition and punishment risks on recent crime trends. In the first section, models of crime, punishment, and youth trends are estimated through econometric methods. They indicate that changes in punishment policy explain these trends while changes in the population's age composition do not. Some limitations of the analysis are discussed and some attempts are made to extend the findings. Using victimization data on offender characteristics, a second analysis assesses the merits of other evidence supporting age-based explanations of crime trends. It finds -- to the contrary -- that youths are disproportionately active in crime and that changing age patterns in the population should account at least in part for crime trends. A concluding analysis attempts to isolate the explanatory power of age trends by forecasting crime rates over the 1960 - 1983 period. It finds that forecasts based on age composition alone explain little of the past 24 years' crime trends.

Time-Series Data and Methodology

Data used in the time-series investigation consisted of nationally aggregated statistics on crime rates, punishment policies, and youth populations. They were available for all variables for the time frame 1960 - 1983.[1] Five variables were constructed: so-called Index, or Part I crime rates - Y; clearance rates (fraction of crimes cleared by arrest) for Part I crimes as a measure of arrest risk - P(A); imprisonment rates per crime - P(I); imprisonment rates per arrest P(I|A); and fraction of the U.S. population male aged 15 - 19, M. Summary statistics are given for each variable in Table 1.

Crime rates were taken directly from Uniform Crime Reports; male youth populations were taken from Bureau of the Census population reports. Clearance rates for later years were taken directly from UCR tables. Rates for the years 1960 to 1967 had to be constructed as a weighted average of the crime-specific clearance rates reported; weights were the number of crimes in each category (i.e., homicides x homicide clearance rate, etc.). Probability of imprisonment for a crime was computed by dividing prisoners per capita (as given by U.S. Prisoner Reports) by crimes per capita (as given by Uniform Crime Reports). Conditional rates of imprisonment given arrest were computed by dividing probability of imprisonment P(I) by probability of arrest P(A). These procedures were necessary to create three nationally representative measures of punishment risk.

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Crime Rate---Y	0.0397	0.0139	0.019	0.059
Arrest Rate--P(A)	0.2191	0.0235	0.192	0.267
Prison Risk--P(I)	0.0334	0.0136	0.021	0.063
Prison/Arrest-P(I|A)	0.1485	0.0433	0.099	0.239
Males 15-19--M	0.0459	0.0038	0.038	0.050

Only five variables were created because of the limited (24-year) length of the time series available. In general, analyses were limited further to a comparison of the effects of each sanction variable relative to the effects of the demographic variable, youth males. These pairwise comparisons conserved the maximum degrees of freedom for hypothesis testing.

Three alternative models of offender decision-making were constructed in order to test the sensitivity of findings to model perturbations. The simplest model was one of contemporaneous decisionmaking: crime rates depend on current punishment risks and the relative size of the male youth population. A second specification embodied the notion that offenders act on last year's punishment risks; that is, information is lagged one year. The third specification captured the notion of adaptive expectations. Offenders are assumed to update their expectations about punishment risks and adjust their

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[1] The FBI revised its time series on Part I crimes in 1973. In order to provide comparability among prior reports, they revised their index crime series back to 1960. Years prior to 1960 do not connect smoothly to the revised series.

crime-commission rates in proportion to the difference between current observed risks and last year's expected risks.[2] These specifications are given by equations 1 - 3. The variable x_t represents the year t value of one of the punishment probabilities; y_t is the crime rate in year t; m_t the fraction of males aged 15 - 19.

(1) $y_t = \beta_0 + \beta_1 x_t + \beta_2 m_t + u_t$ (Contemporaneous Decisions);

(2) $y_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 m_t + u_t$ (Lagged Information);

(3) $y_t = \beta_0 + \beta_1 x_t + \beta_2 m_t + \beta_3 y_{t-1} + u_t$ (Adaptive Expectations).

All variables were transformed by their natural logarithms for a number of reasons. The economics postulate that decisions are based on diminishing marginal utility for rewards (or disutility for punishment) argues for a functional form having a positive first derivative (more is better) and a negative second derivative (progressively diminished satisfaction) with respect to the reward variable. Logarithms fulfill these conditions. From an empirical standpoint, the transformation alleviated some of the multicollinearity among the independent variables. A final consideration was ease of interpretation of the results. The estimated coefficients of the independent variables are directly interpretable as the percentage change in crime rates predicted by a one percent change (at the mean) in the independent variable.

Both the contemporaneous decisionmaking and the lagged information models (equations 1 and 2) were estimated by an ordinary least squares regression approach. In order to correct for serial correlation among the observations, a Cochrane-Orcutt (1949) iterative correction was incorporated into the estimation process.

A number of plausible assumptions can be made about the structure of the disturbance term and each assumption suggests a different estimation procedure. Because serial correlation coefficients were extremely high in earlier estimations, a more general structure than that of equation 3 was assumed. It accommodated the structure implied by the adaptive expectations model but also recognized the findings of earlier estimations. The error structure in equation 3 was replaced by equation 4:

(4) $u_t = \phi u_{t-1} + v_t \quad (|\phi| < 1).$

Equation errors now depend on the error of the previous period plus a random component v_t which is assumed to be uncorrelated with those errors, be normally distributed with constant variance across all observations.

Introducing a lagged dependent variable into the model meant that u_t was no longer uncorrelated with all explanatory variables. Estimating equation 3 by ordinary least squares would yield biased parameter estimates in small samples. An instrumental variables approach was taken to treat this defect.

The first step was to eliminate the correlation between y_{t-1} and u_t. The model in equation 5 was estimated by ordinary least squares.

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[2] See Johnston, Econometric Methods (2nd edition) for a discussion and derivation of adaptive expectations and related models.

(5) $y_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 m_{t-1} + w_t$.

The coefficients estimated were then used to predict y_{t-1}. The predicted values were substituted into equation 3 to produce an explanatory variable that was uncorrelated with the error term. Equation 3 was then estimated with correction for serial correlation. Results are displayed in Table 2.

Findings and Limitations

The most striking feature of Table 2 is that no model displayed a significant demographic effect. On the other hand, the deterrence variables were nearly always significant. All regressions exhibited high general explanatory power -- adjusted R^2 of 0.98 or better -- and high correlations among the consecutive observations -- estimated serial correlation coefficients between 0.94 and 0.96. Lagging crime rates produced no departures from earlier qualitative conclusions. If anything, adaptive expectations models were more supportive of the importance of punishment risks in influencing crime rates than the earlier estimations.

Informative comparisons between these results and other results in the literature were not always possible because of differences in the definitions of the deterrence and demographic variables. Some comparisons were possible nonetheless. They indicated that the deterrence estimates obtained in these models were similar to those found by other studies: a one percent increase in a probability of punishment predicted a decrease in crime rates equal to or less than one percent. Clearance rate -- P(A) -- has been a commonly used indicator of apprehension risk. Pogue (1975) reported a significant clearance rate coefficient of -0.959 against all crimes and Sjoquist (1973) a significant coefficient of -0.352 in a study of property crimes. Zedlewski (1983) reported non-significant findings for property crimes with FBI estimates of clearance rates but large (-1.759) and significant coefficients with victimization-based clearance rates.[3] All three studies were cross-sectional. Wolpin (1978) reported a significant coefficient for imprisonment risk P(I) of -0.785 in a time-series study of comparable crimes in England and Wales. Ehrlich (1973) reported a significant coefficient for P(I) of -0.991 in a cross-sectional study of states using 1960 data.

Related demographic results have been inconsistent but in general not supportive of age-based explanations of crime rates. Ehrlich's study found that the percent of males aged 14-24 was sometimes a significant explanatory variable, with an estimated coefficient as large as 1.157. Pogue (males aged 18-25), Wolpin (males aged 10-25), and Zedlewski (males 16-24) reported nonsignificant associations between youth populations and crime rates. Substituting percent males aged 15 - 24 for males aged 15 - 19 in the analysis above altered none of the qualitative conclusions.

[3] Victimization-based clearance rates divide the number of clearances of a given crime category within a locality by the number of victimizations for that crime estimated by the National Crime Surveys.

Table 2. Alternative Models of Deterrence and Age Composition
Dependent Variable = UCR Crime Rates 1960-1983

A. Contemporaneous Decisionmaking

Const.	P(A)	P(I)	P(I|A)	M	Adj.R^2	D-W
-3.41	-1.15*	--	---	0.36	0.99	1.26
(1.63)	(3.79)	--	---	(0.67)		
-7.35	--	-0.66*	---	-0.76	0.99	1.05**
(4.01)	--	(6.41)	---	(1.71)		
-6.86	--	--	-0.76*	-0.88	0.99	1.30
(3.05)	--	--	(4.40)	(1.53)		

B. Lagged Information

Const.	$P(A)_{-1}$	$P(I)_{-1}$	$P(I\|A)_{-1}$	M	Adj.R^2	D-W
-2.46	-0.32	---	---	0.27	0.98	1.27
(0.96)	(0.79)	---	---	(0.36)		
-4.50	---	-0.37*	---	0.11	0.98	1.59
(1.70)	---	(2.58)	---	(0.15)		
-5.03	---	---	-0.54*	-0.36	0.98	1.65
(1.96)	---	---	(3.00)	(0.50)		

C. Adaptive Expectations

Const.	P(A)	P(I)	P(I|A)	Y_{-1}	M	Adj.R^{2}***
-3.62	-1.09*	--	--	0.02	0.30	0.98
(1.56)	(3.11)			(0.15)	(0.46)	
-7.44	--	-0.64*	--	0.02	-0.81	0.99
(3.54)		(5.30)		(0.25)	(1.50)	
-7.65	--	--	-0.76*	0.07	-1.16	0.98
(3.16)			(4.28)	(0.57)	(1.66)	

* t-ratios in parentheses. Significant at 0.01 level of one-sided test.
** Durbin-Watson statistic rejects hypothesis that serial correlation has been eliminated at 0.05 level of confidence.
*** Durbin-Watson tests can not be applied to models with lagged dependent variables.

Several possible challenges can be advanced for the results obtained, not the least of which is the highly aggregated and limited duration of the time series. National crime statistics undoubtedly mask rich variations in state and local trends that might produce contrary conclusions. The 24-year duration of the series precluded consideration of more sophisticated portrayals of socioeconomic factors such as the representation of temporal changes in incomes or employment opportunities, or increasing urbanization. Adding to these data limitations is the presence of multicollinearity among the variables actually used, a factor that could have masked demographic influences.

Aggregation errors are an inherent limitation of the data that could not be treated. Other limitations, which were addressed with varying degrees of success, are described below.

Attempts to adjust for the combined temporal and inter-variable error correlations were not fully successful. Durbin-Watson statistics indicated that one estimation of a contemporaneous decision-making model had not corrected fully for serial correlation; in other estimations the tests for serial correlation (after corrections) were inconclusive. Even though serial correlation doesn't bias estimates of regression coefficients, it tends to underestimate their variances and inflate t-statistics. Variables reported as significant explanatory factors might not actually be so.

In order to estimate the relative importance among risk measures in explaining crime rates, each model was re-estimated using pairs of the three risk indicators in addition to the youth variable. One or both of the punishment variables remained consistently significant, but the coefficients tended to vary markedly from run to run, suggesting that multicollinearity had become so severe a problem that estimates of the relative importance of these risks were unreliable.

Ehrlich (1973) first noted that models which regress crimes rates against punishments (arrests or imprisonments) per crime were biased in favor of finding deterrent effects. The estimated deterrence coefficient will tend to be negative even if the true relationship between crime rates and punishment risk is zero because of errors in the measurement of crime rates. Taylor (1978) showed that the general effect for logarithmic specifications was to bias punishment coefficients toward -1. The presence of this statistical artifact suggests that deterrent effects might actually be smaller than estimated. However, the artifact does not occur in $P(I|A)$ -- prisoners **per arrest** -- which was consistently significant.

It is also possible that two phenomena are operating simultaneously to determine crime rates and punishment risks. It may be that crime rates are influenced by punishment risks but, at the same time, punishment risks are being influenced by crime rates and other factors.

Models were built to test the effects of crime rates and demographics on punishment risks. These models supposed that police resources for solving crimes were being fully utilized and that prison capacity was almost fully absorbed by current confinements. Then increases in crimes (brought about by increases in youth populations) might reduce either the percentage of crimes solved or the percentage of crimes punished. Arrest rates and imprisonment rates would fall through an increase in the denominator -- crimes -- combined with a relatively fixed numerator -- arrests or confinement spaces. The correct causal model to investigate under these assumptions would make punishment risk vary with and youths and crime rates.

In order to factor "saturation" effects into the crime rate function, a two-stage model was estimated. Each punishment variable was regressed against youth variables, correcting for serial correlation. A predicted value was computed for x_t as given by equation 6 and substituted into equation 7. Equation 7 was then estimated with a correction for serial correlation.

(6) $x_t = \beta_{01} + \beta_{11}m_t + \beta_{21}m_{t-1} + u_t$; and

(7) $y_t = \beta_{02} + \beta_{32}x_{t-1} + \beta_{12}m_t + v_t$.

Crime rates were negatively associated with all deterrence indicators and youths had a negative effect on imprisonment rates. Omitting crime rates from the specification produced negative and significant youth coefficients (at a 0.05 confidence level) for P(I) and P(I|A) but not P(A). Unfortunately the exercise failed after the first step. Estimations of equation 7 were unstable: coefficients had very large t-statistics, sometimes with improper signs, yet there was an overall reduction in explanatory power of the models.

Support for a saturation hypothesis adds to the understanding of how enforcement activities and resources involved in producing deterrence are affected by workloads. It does not necessarily contradict findings of deterrence effects. It is possible that the true magnitudes of deterrent effects are simply being overestimated. Even if saturated law enforcement resources diminish levels of punishment risk offenders may respond to whatever levels of risk they estimate to be operating.

The limitations of the analyses conducted do not discredit the policy implications entirely. They do, however, caution against sweeping statements to the effect that certainty of punishment is the way to reduce crime rates. Moreover, the limitations apply only to the reliability of deterrence findings. They do not imply that, by partial default, demographics are an alternative explanation for recent crime trends.

Some Contrary Evidence

The evidence reviewed in the realm of econometric studies offered little empirical support for youth-based explanations of crime trends. But these studies are not the primary bases for demographically-inspired hypotheses. Rather, youth-based explanations of crime rates derive support from two other classes of investigations: self-reports on criminal activities by juveniles and the overrepresentation of youths among arrestee populations. This analysis conducted in this section uses arrest-based statistics to infer the effects of age composition on crime trends.

The so-called "aging-out" phenomena has been widely recognized in criminology literature. Most recently, Sviridoff and McElroy (1984) describe a process by which youths reduce their criminal activities as legitimate opportunities open up to them. Not surprisingly, these legitimate earning opportunities increase in abundance with age. Self-report studies support a contention of relatively wide-spread involvement by youths in crime. But they do not necessarily imply that youths are responsible for a great deal of serious crime.

To estimate the contributions of youth populations to crime rates it is necessary to know how many youths are involved in any given crime. If, for example, each of three youths reports an involvement with a robbery but research establishes that on average three youth are involved in every youth robbery, then the "crime output" implied by self-reports is but one robbery. Similar distinctions between prevalence -- the extent of participation in an activity -- and incidence -- the intensity of activity -- are drawn by Reiss (1982) in the same issue of age effects and by Blumstein and Graddy (1982) in the study of racial differences in recidivism. Zimring (1981) cites three studies that have found youth crime to be a group affair. While they differ by crime type and points in time, the three estimates of the average number of youths per crime were in fair agreement: Shaw and McKay (1928) -- 2.79 per offense in juvenile court; National Crime Panel (1973) -- 2.18 per robbery (versus 1.53 per adult robbery); and Rand Corporation's Juvenile Record Study (1979) -- 2.36 per robbery. The 1973 Crime Panel and Rand averages are biased downward because of truncation at the upper end on counts of participants.

This logic extends directly to analyses of arrest statistics. If the probability of arrest for a given type of crime is independent of age and if the number of persons arrested is also independent of age, then arrests are useful surrogates for underlying crime-commission rates of various age cohorts. But if youths tend to be arrested in groups and adults tend to be arrested singly, then disproportionate representation of youths among arrestee populations will distort estimates of their crime contribution.

To shed light on the potential bias induced into youth contributions to crime rates, estimates were derived of how propensities for group crimes changed with the ages of perpetrators. Estimates of the relative frequencies of multiple offender crimes and the number of participants per crime were taken from the 1983 National Crime Survey. Victims of crimes involving personal contact -- rapes, robberies, assaults, purse-snatchings, pocket-pickings, etc. -- were asked to identify the ages, races and sexes of offenders who victimized them.[4] These responses were available for the age categories given in Table 3. As is evident the propensity to engage in group crimes declines with ages 15 - 20. Approximately one in four or five crimes committed by youths involved accomplices; this frequency declined to less than one in ten for the oldest age group.

Table 3. Offense Participants Per Crime By Age
(National Crime Surveys - 1983)

Age Group	Number of Participants Reported 1	2	3	4+	Other	(Pct.) Total
10 - 14	81.3	9.9	3.4	4.7	0.8	100.0
15 - 20	76.7	13.3	6.3	3.5	0.2	100.0
21 - 29	86.6	9.0	2.4	1.7	0.3	100.0
Over 30	91.6	6.9	1.0	0.4	0.1	100.0

The average number of participants per crime was computed from these frequencies for each age group. These averages were used as a measure of arrests per crime to convert relative arrest frequencies for Part I crimes (as reported in the 1983 Uniform Crime

[4]About 80 percent of the crimes involving youths and 90 percent of the crimes involving adult offenders reported by survey victims were violent crimes. However, the average number of participants per crime was roughly the same for property and violent crimes within an age group.

Reports) into implicit relative crime frequencies. Arrests per age group were divided by participants per crime to yield crimes per age group. Results are displayed in Table 4.

Table 4. Crime Outputs By Age Group

	Age Groups			
	10 - 14	15 - 20	21 - 29	30 - 99
A. Arrests	261,076	625,077	509,752	378,854
B. Males (000)	9,091	11,978	19,587	56,228
C. A/B (Pct.)	2.9	5.2	2.6	0.7
D. Part. Avg.	1.3	1.4	1.2	1.1
E. C/D	2.2	3.8	2.2	0.6

Row E estimates the relative number of offenses (resulting in an arrest) committed per male after adjustment for participants per offense. The two to one ratio between arrest rates in the cohorts aged 15 - 20 and 21 - 29 was only slightly offset by the ratios between the average numbers of participants per crime. Crime rates implied for 10 - 14 year olds are identical to those implied for young adults. Thus the size of the 15 - 20 year old cohort appears to be a determinant of crime trends.

The evidence from the 1983 National Crime Surveys supports demographic arguments but it too has its limitations. The average numbers of participants per crime found there are strikingly lower than those cited by Zimring. The differences from the 1973 Crime Panel -- a similar data source -- are particularly troublesome. While it is possible that youths have moved away from group crimes, the differences between the sources seem too large to be explained by that hypothesis alone.

Another possible explanation for differences in implicit cohort crime rates is that arrest risk may not be independent of age and might in fact be higher for younger populations. Virtually every occupation is practiced more skillfully with experience, at least to a certain point. It seems reasonable to presume that the crime profession has similar returns to experience in the sense that older criminals are less likely to be caught. Deflating arrest statistics to account for average number of participants would not adjust for experience effects.

Other factors may also work to increase the apprehension rates of youths relative to those of adults. Sviridoff and McElroy found that youths committed the majority of their offenses in or about their own neighborhoods, where they were more likely to be recognized at the crime scene or during subsequent disposition of their gains. Moreover, the likelihood of recognition increases with the number of participants. If there are n participants in a crime there are n persons who can be recognized either by neighbors or parents and more potential "stool pigeons" who can turn in accomplices if caught. If the probability of being identified as a single perpetrator of a crime is p, then the probability that one or more of n participants are identified is approximately np if probabilities of identification are independent.

This discussion suggests that changes in age composition may affect crime rates but more restrictively than supposed. Youths do appear to be disproportionately involved in crime but not at every age. The evidence developed here suggests that crime activity increases in the mid-teens and then recedes to a pre-teen level at adulthood. Apart from the 15 - 20 year old cohort, imputed crime rates were roughly constant for ages 10 - 30. It is worth noting that the period of intensification coincides with the transition from school to the young adult work force.

Demographics and Crime Forecasts

Given that age composition is a determinant of crime, is it powerful enough a determinant to forecast crime trends? A simple age-based model of crime trends was constructed to explore this question.

Crimes were imputed to various age groups in proportion to the fraction of arrests experienced by each age group. The crimes imputed to an age group were divided by its population to produce an incidence rate, or number of crimes committed per capita. Table 5 gives these statistics for 1983 Part I crimes and populations.

Table 5. Cohort Incidence Rates -- 1983

Age	10 - 14	15 - 19	20 - 24	25 - 29	Over 30	Total
Population(000)	17,781	19,210	21,925	21,219	120,552	200,587
Arrest Fraction	0.120	0.303	0.207	0.138	0.232	1.000
Part I Crime(000)	1,453	3,653	2,504	1,671	2,789	12,070
Incidence Rate (per thousand)	81.74	190.16	114.20	78.75	23.14	60.17

Corresponding population figures for prior years were assembled from Bureau of Census population estimates. Incidence rates for 1983 were multiplied by these corresponding populations to estimate total Part I crimes for selected prior years. Not surprisingly, forecasts deteriorated progressively as the time from the base year 1983 increased. The 1963 forecast was more than twice the actual crime count for that year.

Table 6. Age-Based Crime Forecasts: 1983 - 1963

Year	1983	1978	1973	1968	1968
Forecast ($x10^6$)	12.07	12.03	11.35	10.16	8.87
Actual ($x10^6$)	12.07	11.17	8.72	6.72	4.11

Several explanations for the wide divergences exist. One is that age composition shifts slowly relative to other social phenomena. The U.S. population grew by only 24 percent over the forecast period. Even with substantial shifts in age composition brought about by the passing of the baby boom, the range on crime forecasts was only 36 percent. In contrast, actual crime counts grew by 194 percent.

Another possible explanation is punishment policy. The econometric results presented earlier found significant negative associations between various indicators of punishment risk and crime rate. These factors are omitted in the simple age-based model.

It is reasonable to assume that the deterrent effectiveness would vary with age composition because punishment policies are often age-related. The simplest illustration of this dependence is the difference in attitudes toward punishment in the juvenile and adult justice systems. Thus, punishment policy and demographic trends should not act additively to explain crime rates. Rather, one should expect an interaction between age composition and the ages targeted for punishment.

Another possible explanation for the divergence of predicted crime rates from actual rates is that cohort-specific incidence rates have changed over time; specifically, rates of criminal involvement have increased over the 1963 - 1983 period. Part of such an increase could be attributed to changes in criminal opportunity brought about by increasing urbanization and changing family structures. Another part might be attributed to changes in norms for socially acceptable behavior. Of course, changes in the risks attached to criminal acts would also account for changes in the frequency of such behavior.

Finally, a simple age-based model ignores too many other important demographic factors. To the extent that minority groups are a useful surrogate for disadvantage populations, their representation in the general population may help explain crime trends. Nonwhites represented 11.3 percent of the population in 1960; nonwhites age 14 - 24 were 12.2 percent of their age cohort. Through a combination of births and migrations, nonwhites comprised 14.8 percent of the population in 1983; nonwhites aged 14 - 24 were 17.1 percent of their cohort. Minority populations have increased, but not sufficiently to account for the 175 percent increase in crime rates.

The data used in these analyses are too simple to test competing theories about the weakness of age-based forecasts; they are only sufficient to show that these forecasts explain relatively little crime in the absence of any behavioral theory about why propensities to commit crimes have risen.

Summary

One might interpret this paper as testing a spectrum of hypothetical statements about the effects of demographics (age composition) on crime: "Age doesn't matter."; "Age matters a little."; Age matters."; Age matters a lot."; and, "Only age matters." If so, then the findings support statements near the early end of the spectrum. Bases for this assessment are highlighted below.

In an econometric test of the relative explanatory power of deterrence and demographic variables, nearly every model specification revealed negative and statistically significant associations between crime rates and punishment risks. No direct support for a demographic basis for crime trends was found. On the other hand, it would be impossible to conclude from the findings that deterrence doesn't work. Data limitations notwithstanding, the pervasive explanatory power of the three punishment indexes used supports the use of deterrence oriented crime control policies. The consistent performance of the conditional probability of imprisonment given arrest, which does not suffer from estimation bias when regressed against crimes per capita is particularly noteworthy.

An inquiry into the effects of group crime among youth populations demonstrated that the supposed youth influences on crime rates can't be made to disappear by accounting for the number of youths involved in a given criminal event. While the evidence is modest, it suggests that youths do indeed account for some portion of the rising crime experienced over the 1960s and 1970s.

A final investigation explored the ability of changing age compositions to forecast crime trends over the 1963 - 1983 period. It found that, when incidence rates within age groups were held constant, age-based forecast diverged quickly from actual crime trends. This divergence was taken as evidence that age must be combined with other factors to produce reasonable crime forecasts.

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Appendix - Raw Data

Year	UCR Index[a]	P(A)[b]	P(I)[c]	P(I|A)[d]	Males[e]
1960	0.018758	0.261	0.06237	0.2390	0.0377
1961	0.018945	0.267	0.06281	0.2353	0.0379
1962	0.020076	0.257	0.05828	0.2268	0.0406
1963	0.021670	0.251	0.05261	0.2096	0.0415
1964	0.023737	0.245	0.04676	0.1909	0.0429
1965	0.024342	0.246	0.04437	0.1804	0.0445
1966	0.026547	0.243	0.03842	0.1581	0.0464
1967	0.029718	0.224	0.03298	0.1472	0.0458
1968	0.033502	0.209	0.02806	0.1342	0.0463
1969	0.036581	0.201	0.02652	0.1319	0.0470
1970	0.039608	0.201	0.02424	0.1206	0.0479
1971	0.041400	0.197	0.02295	0.1165	0.0484
1972	0.039378	0.206	0.02362	0.1146	0.0491
1973	0.041297	0.212	0.02325	0.1097	0.0497
1974	0.048214	0.213	0.02116	0.0993	0.0500
1975	0.052817	0.210	0.02102	0.1001	0.0501
1976	0.052717	0.205	0.02276	0.1110	0.0502
1977	0.050620	0.210	0.02509	0.1195	0.0497
1978	0.051443	0.208	0.02576	0.1238	0.0491
1979	0.055481	0.198	0.02397	0.1211	0.0484
1980	0.059313	0.192	0.02327	0.1212	0.0473
1981	0.058410	0.195	0.02619	0.1343	0.0454
1982	0.055861	0.201	0.03043	0.1514	0.0437
1983	0.051586	0.206	0.03470	0.1684	0.0418

a. Crime rates per capita. Uniform Crime Reports 1974, 1983.

b. Clearance rates - all Index Crimes. Uniform Crime Reports 1960 - 1983. Computed as weighted average of index crime rates for 1960 - 1966. Taken directly from tables thereafter.

c. Imprisonment risk. Prisoners per 100,000 population (Bureau of Justice Statistics Bulletin Prisoners 1925-1981, December 1982, updated by 1982 and 1983 bulletins) divided by UCR index crimes per 100,000 population.

d. Imprisonment risk given arrest. Raw imprisonment risk divided by clearance rates.

e. Fraction of population of males aged 15 - 19. Current Population Reports, Population Estimates and Projections, Series P-25. Bureau of the Census. No. 519 (April 1974) for 1960-1969; No. 917 (July 1982) for 1970-1979; No. 949 (May 1984) for 1980-1983.