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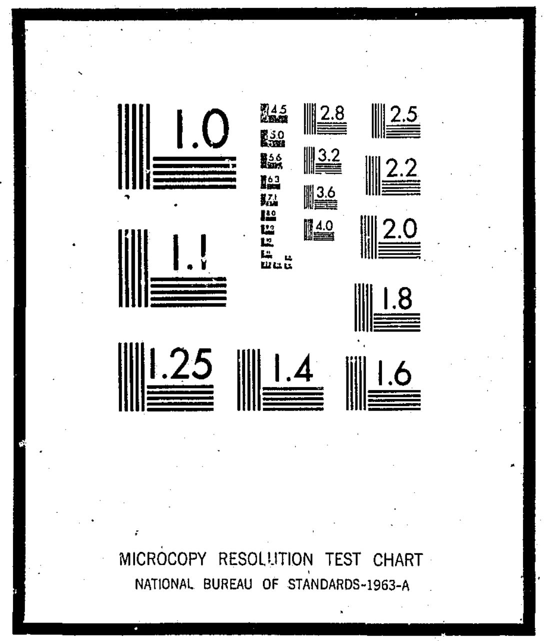

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ON URBAN HOMICIDE: A STATISTICAL ANALYSIS

by

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FOREWORD

The research project, "Innovative Resource Planning in Urban Public Safety Systems," is a multidisciplinary activity, supported by the National Science Foundation, and involving faculty and students from the M.I.T. Schools of Engineering, Architecture and Urban Planning, Management, and Mathematics. The administrative home for the project is the M.I.T. Operations Research Center. The research focuses on three areas: 1) <u>evaluation criteria</u>, 2) <u>analytical tools</u>, and 3) <u>impacts upon traditional methods</u>, <u>standards</u>, <u>operating procedures</u>, <u>and perceptions of urban risk</u>. The work reported in this working paper is associated primarily with category 3, and focuses on the development of new statistical measures for computing risks of victimization.

Richard C. Larson
Principal Investigator

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On Urban Homicide

ABSTRACT

A statistical analysis is made of homicide rates in the 50 largest American cities for four different years. It is shown that differences in recent murder growth among the cities can largely be explained as typical random fluctuations about a common trend. It is also found, among other things, that the changing age profile of the American people explains no more than 10% of the increase in homicide since 1964. Several mathematical models for future homicide growth are proposed from the analysis, and under each the probability of death by murder and corresponding drop in life expectancy are estimated for babies born now in each of the 50 cities.

On Urban Homicide

Introduction

The concern about the crime problem in America is perhaps exceeded only by the confusion about it. There is great controversy over the accuracy of crime statistics; even Attorney General Richardson was skeptical as he released the 1972 F.B.I. figures. And there is bitter disagreement over what the statistics mean even if they are accepted at face value. We might, as has been suggested, be close to "turning the corner" on crime, but it is somewhat unclear what we should expect to find there.

We concern ourselves in this paper with the most terrible of all crimes - murder. The homicide rate in the U.S. has been rising in recent years, and this fact has become increasingly important in American political life. Detroit's reputation as the "murder capitol of the world" figured prominently in its recent mayoral election. Polls show that an increasing majority of Americans now favors capital punishment, and that the rise in murder is a major reason. (Twenty-one states have passed new mandatory death penalties in the last eighteen months.) Governer Rockefeller of New York cited the recent trends in killing in calling for very harsh drug control laws. Gun control advocates regularly note the rising murder toll in their arguments.

The public policy implications of the climbing homicide rate make it particularly important that people have an accurate view of the magnitude of the problem. Yet the annual homicide totals, although probably the most reliable of all crime statistics, are misleading and unsatisfactory as indices of the situation. As has often been noted, rises and falls in the total number of murders do not necessarily correspond to changes in the dangers individual citizens face. (Indeed, it is theoretically possible for the homicide rate to increase (or decrease) significantly without any corresponding change in the murder risk for ANY citizen; see 1.) And, quite apart from this problem, the risk implications of the annual statistics may be orders-of-magnitude different than they might seem. Roughly 250 residents of Atlanta were murdered in 1973, but this number is small compared to the roughly 500,000 citizens of that city who were not murdered. Few people realize that, if this rate continues, homicide will be the cause of death of roughly 1 of every 27 Atlantans.

Because of the difficulty in assessing the homicide problem with annual statistics, some new standards have been proposed for measuring the danger. (1) One such standard is the answer to the question: what is the probability that a randomly chosen baby born now in a given city, who lives there all his life, will eventually die of murder? Another index is the decrease in life expectancy of this baby because of homicide. Either of these numbers, if known, would presumably indicate in a meaningful way the amount of homicide in the city considered.

It is not difficult to obtain mathematical expressions for these quantities, but these expressions necessarily depend on homicide rates in the future. These rates cannot of course be known precisely now, but if one were to use projections based on sensible mathematical

models in the appropriate equations (which were derived in 1), presumably some reasonable estimates of homicide risk would result. It is the purpose of this paper to formulate such mathematical models and to employ them to measure the danger of homicide in each of the 50 largest American cities.

There are many questions we must consider before making projections about future homicide. Among them are: what correlation, if any, might we expect between changes in the murder rates in such disparate cities as Milwaukee and Detroit? What change, if any, might we anticipate in the age distribution of homicide victims in the future? (This is important since the hypothetical baby whose homicide risk we are estimating is continuously getting older.) How closely is the homicide rise tied to the swelling fraction of Americans at the ages when the tendency to commit murder is greatest? Can we discern some "inner dynamic" of homicide growth that would lead us to expect saturation levels or ever-increasing acceleration?

We attempt to answer these and other questions by analyzing data on homicide in each of the 50 largest U.S. cities for four different years, and considering the aggregate homicide rate in America over the last forty years. Among the conclusions of the analysis are:

1) During the current period of homicide growth, which began about 1964, the increase in "risk factors" has been fairly uniform among different age groups and ethnic groups. Moreover, the differences in the extent of murder growth in the 50 largest American cities can largely be explained as typical random fluctuations around a common trend.

2) Theories about the rise in murder which relate to phenomena which are not common to most large American cities are difficult to sustain with the available data. 3) The popular view that the current problem is largely rooted in the high birth rate following World War II is untenable, for this phenomenon can account for only about 10% of the rise in murder that actually occurred. With these findings, we generate a set of "postulates" about future homicide levels which in turn are used to develop four models for the evolution of murder rates. The models range from highly optimistic (compared to present levels) to somewhat pessimistic.

The paper concludes with the calculation, under each of our four projections, of the probability of being murdered and the associated decline in life expectancy for a baby born in 1974 in each of our 50 largest cities. The results are not likely to please many readers. We find that, even at current levels, approximately 2% of the babies born now in large American cities will be murdered. The actual figure might reach as high as 5%. Thus, far from suggesting that the current fears are exaggerated, the results imply that homicide in urban America is probably far more prevalent than we ever had realized.

The Recent Homicide Pattern

From the early 1930's, when the FBI began compiling crime statistics, to the mid-1950's, the homicide rate in the United States declined slowly but steadily. There is some evidence that

this was the continuation of a trend which started perhaps as early as the end of World War I. (2) Homicide levels remained fairly constant from about 1955 to the mid 1960's, when a period of rapid increase began. In the last eight years, the rise in murder rates has more than "wiped out" the accumulated decline of the previous forty.

It is important for our purpose to find out the characteristics of the recent homicide growth. To do this, we first calculate the changes in homicide rates since the mid-60's in each of the 50 largest American cities. (According to the 1970 census.) We use as a base rate the number of murders per 100,000 citizens averaged for the years 1963 and 1965, and contrast this number with the comparable quantity for 1971 and 1972. The use of two-year periods is intended to reduce the effects of year-to-year random fluctuations in the number of murders. We do not assume, however, that this procedure has totally eliminated such effects, a point of considerable importance later on.

Immediately the question arises of how we should compare the two homicide rates obtained in each city. The simple calculation of percentage change from the earlier period to the later one is not totally reasonable because of certain demographic realities. Studies by the FBI, President Johnson's Commission on Law Enforcement (2), the Rand Corporation (3) and The New York Times (4), among others, have demonstrated the fact that murder victimization rates are substantially higher among some ethnic groups than others; thus changes in the demographic makeup of a particular city might in themselves be expected to cause major changes in its homicide rate. Since the ethnic composition of many cities has been greatly altered in the last decade, a demographically-adjusted index would be desirable.

The calculation of such an index is not at all difficult; we proceed below for the case when exactly two groups are considered. For a certain city in 1963-65, suppose a is the murder victimization rate for members of group I, X is the fraction of the city's inhabitants in group I, and b is the homicide rate in group II. Then the city's overall homicide rate r_1 for the period satisfies:

$$r_1 = aX + b(1-X)$$

Now suppose that fraction $\tilde{X}$ of the city's residents in 1971-72 are in group I, and that the murder rate in that group has been magnified by factor Ω since 1963 and 1965. If the corresponding multiplier for group II is γ, the homicide rate r_2 for 1971-72 follows:

$$r_2 = \Omega a\tilde{X} + \gamma b(1-\tilde{X})$$

The data itself allows an algebraic simplication at this point: it appears that the magnification factors for different ethnic groups over the eight-year span are very close to equal. On a national level, for instance, the appropriate multiplier for blacks is within 2% of that for whites, and detailed studies in such cities as New York (4) and Chicago (5) suggest that there is little local deviation from the national trend. The approximation $\Omega = \gamma$ in the last equation leads to the expression:

$$\gamma = \frac{r_2}{r_1\left(1 + \frac{(1-\alpha)(\tilde{X}-X)}{\alpha + X(1-\alpha)}\right)}$$

where $\alpha = b/a$. Thus $\left(1 + \frac{(1-\alpha)(\tilde{X}-X)}{\alpha + X(1-\alpha)}\right)^{-1}$ is the correction factor which should be applied to the r_2/r_1 ratio to get an appropriate growth multiplier for the city's homicide rate. The extension to three or more distinct groups is straightforward. The homicide rates for the 50 largest cities (listed in order of decreasing size) in the two periods considered are shown in Table 1, followed by the demographically-adjusted magnification ratios.

We see from the table that homicide rate increased in every single one of the 50 cities. The adjusted growth factors varied from 1.28 (Kansas City) to 3.39 (Detroit). The average of the growth factors was 2.01 and their median value was 1.92; fully 39 of the ratios were within .5 of this latter value. Actually, the amount of variation which arose in the multipliers is not terribly large if we consider that each ratio could in principle have taken any nonnegative value and if we consider further that, because of random fluctuations, some variations would appear in the observed changes even if the same underlying trend prevailed in all cities.

Randomness in Murder Levels

It is desirable at this point to attempt to quantify the notion of random effects in homicide rates. The underlying premise is that the number of murders in a city can vary from year to year due to chance alone, much as annual rainfall varies. Even if, for instance, an individual is by some definition "murder-prone," it is uncertain whether circumstances will arise in a given year which will cause him to kill someone. Suppose that at the beginning of a calender year there is associated with each of the N individuals who lives in or

Table 1: Changes in Homicide Rates in the 50 Largest American Cities+

City	(c) 1963 and 65 homicide rate++	(d) 1971-72 rate++	Demographically-Adjusted Ratio of (d) to (c)
New York	7.49	20.28	2.24
Chicago	10.83	22.78	1.83
Los Angeles	8.38	16.51	1.80
Philadelphia	8.11	21.74	2.44
Detroit	9.64	38.93	3.39
Houston	11.33 ✓	24.19	2.05
Baltimore	14.77	36.08	2.15
Dallas	15.44	24.81	1.47
Washington	15.44	34.39	1.92
Cleveland	11.99	38.47	2.83
Milwaukee	3.39	7.53	1.92
San Francisco	6.68	12.78	1.77
San Diego	3.20	4.88	1.46
San Antonio	7.43	15.29	2.02
Boston	7.56	17.16	1.93
Memphis	7.14	17.42	2.39
St. Louis	17.01	34.16	1.72
New Orleans	11.52	23.52	1.87
Phoenix	7.08	11.56	1.67
Columbus	4.65	11.86	2.45
Seattle	4.02	7.92	1.84
Pittsburgh	5.62	10.96	1.83
Denver	9.18	16.63	1.64
Kansas City	12.50	17.16	1.28
Atlanta	18.36	48.79	2.34
Buffalo	3.98	14.94	3.26
Cincinnati	7.52	16.48	1.96
San Jose	2.28	4.83	1.98
Minneapolis	3.48	8.53	2.26
Fort Worth	14.04	25.57	1.69
Toledo	4.35	8.20	1.84
Newark	15.09	36.52	1.98
Portland (O.)	3.71	6.82	1.75
Oklahoma City	6.87	11.92	1.67
Louisville	12.71	22.79	1.59
Oakland	7.16	23.07	2.65
Long Beach (Cal.)	4.26	11.98	2.53
Omaha	4.96	6.92	1.34
Miami	10.88	26.57	2.42
Tulsa	5.16	9.70	1.78
Honolulu	3.04	9.69	3.13
El Paso	2.94	4.19	1.42
St. Paul	2.54	5.81	2.17
Norfolk	9.19	12.99	1.41
Birmingham	15.59	26.25	1.60
Rochester	3.84	10.14	2.14
Tampa	11.13	20.87	1.77
Wichita	3.66	5.60	1.46
Akron	4.29	12.55	2.61
Tucson	3.40	5.89	1.70

\+ Indianapolis, Nashville, and Jacksonville are not included because their boundaries changed drastically in the 1960's; thus we are using 50 of the 53 largest cities

++ Number of murders per 100,000 residents.

near a given city a probability p_i $(i=1,\ldots,N)$ that (s)he will commit murder there that year. Obviously no one could know these p_i's exactly but the concept is still meaningful in the same way that precipitation probabilities in weather forecasts are meaningful. We will not consider multiple murders here for, fortunately, they are still rare. The expected number of murders in that city during the year is $\sum_{i=1}^{N} p_i$ and, making the assumption that the actions of different people are independent in these matters (which would seem approximately true), the variance in the murder toll is $\sum_{1}^{N} p_i - \sum_{1}^{N} p_i^2$. An average value of p_i for most cities is about 10^{-4} and its maximum value is probably .1 or less; thus it seems reasonable to assume that the second summation in the variance is probably negligible compared to the first. Coupled with the Central Limit Theorem, these considerations lead us to speculate that the actual number of homicides in a year is approximately a normally distributed random variable, with its mean nearly equal to its variance.

We will assume, as a working hypothesis, that the number of murders in any city in a particular year is in fact normally distributed with equal mean and variance. The mean itself may of course vary from city to city. We use this assumption in attempting to answer the question: to what extent can the observed differences in the homicide growth factors in Table 1 be explained as random variations around a common trend? If the answer turns out to be "almost fully," it would have important implications for us, for it would suggest a strong correlation between national trends† and those in individual localities, at least in the current growth period. Such information would be useful in projecting future homicide levels, and might also be helpful in evaluating the various theories that have been advanced to explain the current rise in murder.

We deal with the question by using a "uniform growth" hypothesis and then comparing the deviations from uniformity one would expect because of randomness with those that actually arose. Testing the hypothesis is a somewhat complicated matter, for independent (and differently distributed) random variables arise for each of the 50 cities. The statistical procedure used is described in some detail in Appendix A. The analysis enables us to compare a "group portrait" of the actual magnification factors with one assembled from the set of random variables; the results are presented below and indicate rather large similarities between the two outcomes.

1) Based on our assumptions about the randomness in murder levels, the expected value of the largest observed growth multiplier is 3.3.(to the nearest tenth) The expected value of the smallest of the 50 growth factors is 1.3. These numbers compare rather strikingly to the actual high of 3.39 and low of 1.28. In other words, the range of the multipliers in real life was very close to the range we would have anticipated because of random fluctuations alone.

† Throughout this paper, we effectively equate national trends with those of the 50 largest cities as a group. This is reasonable because, especially since urban murder rates are much higher than rural or suburban rates, the national figures are strongly correlated with those from our cities.

2) For normal variat es with mean and variance nearly equal, the average percentage deviation of a sample value from its mean μ is almost directly proportional to $\mu^{-1/2}$. Thus, if our model is correct, we would expect the oscillations of growth factors around 1.92 to be of greater amplitude in those cities with relatively few homicides than in those with higher numbers of murders. (though not necessarily higher homicide rates.) This phenomenon very much occurs in the data; the mean square deviation from 1.92 among the actual multipliers for the 25 cities with the largest homicide totals for 1963 and 65 is .16; that for the other 25 cities with lower totals is .30, almost twice as high. (The medians for both groups individually are almost identical, at 1.92 and 1.90).

3) For the distributions assumed for the s_j's, the mean square deviation g from 1.92 (i.e. $g = \frac{1}{50}\sum_{1}^{50}(s_j-1.92)^2$) is .20. (This is also, almost exactly, the average of the variances of the s_j's.) The actual square deviations had an average of .23. It is significant that, even under further restrictions to avoid influence by extreme values, the standard deviation of g is .04. This means that the average square of the fluctuations that actually appeared is within one standard deviation of the expected value of this quantity under our model.

To be sure there are some noteworthy differences between the predictions of the theoretical model and the actual data. The growth ratios for the four largest American cities - New York, Chicago, Los Angeles and Philadelphia - are as a group somewhat closer to 1.92

than the average distance for the other cities, but their deviations are nonetheless larger than we would expect. (although not astonishingly so) And while the model leads us to anticipate a maximum ratio near the observed maximum of 3.39, it is highly improbable that this highest growth factor would arise in Detroit, the fifth largest city in the country. But to focus on the fact that the hypothesis has some imperfections is to obscure a very important point. The fact is that a uniform growth model that ignores almost every dissimilarity between different cities-in total size, in population density, in political leanings, in geographic region, in unemployment rates, in police departments, in drug-addiction problems, in early-60's homicide rates- comes extremely close to predicting both the magnitude and the nature of the dispersion in growth factors which did occur.

Indeed, a more detailed look at the data seems to confirm what the anlysis suggests- that specific city characteristics are surprisingly unimportant in homicide changes. We find, for example, that the coefficient of correlation of individual growth multipliers with the corresponding 1963 & 65 murder rates is -.12; that with the 1971-72 rates (which is necessary greater) is .28. The "average correlation" of .08 hardly suggest a substantial relationship, especially since the average falls to .03 with the elimination of just one city. (Detroit) And while the magnification ratios for Southern cities averaged about 9% below those for the rest of the nation, it is also true that 5 of the 12 Southern cities - Atlanta, Houston, Memphis, Miami, and San Antonio - had growth factors above the national average, making any theories about Southern tranquility difficult to take seriously. Similar circumstances arise as we

search for other correlations. It would seem that those explanations for the murder "boom" related to national rather than local phenomena would seem stronger in the light of these results; the practical value of this observation, however, is limited. Certain suggested causes of the murder rise (e.g. racial tensions, deteriorations of the core city) would seem weakened by these findings, since they are presumably far more relevant in some cities than others. Yet several other theories (e.g. proliferation of handguns, political violence, greater leniency in the justice system) relate to phenomena which are national in scope yet quite possibly of varying impact in different localities. About such theories we can say very little. The view that the changing age profile of the American population explains the observed trend is considered in detail later in the paper.*

Assumptions about Changes in Homicide Levels

The fact that the cities have moved pretty much the same way during the current period of rising homicide does not mean, of course, that such a pattern will continue. But this trend does make it somewhat more reasonable to assume that the cities will continue to behave similarly than that major differences in homicide growth factors will arise. Hence we arrive at our first assumption concerning future homicide rates.

* Since demographic corrections greatly reduced the differences in growth factors in different cities, one might speculate that the variations in actual homicide rates among the cities are themselves caused by demographic factors. This, however, is not the case.

Assumption 1:

The demographically-adjusted homicide rates for the 50 largest American cities will change in the future in approximately uniform fashion. (i.e. with equal magnification factors) The murder victimization rates for the different ethnic groups in each city will also increase or decrease by the same proportion.

This is, of course, a projection of the behavior of the past 8 years whose analysis has just been described. The last part of the hypothesis indicates why the question of murder risk for a baby born in 1974 can be answered without concern for future demographic changes. Changes in demography under this assumption affect the fraction of citizens in each "risk category" but not, under our assumptions, the danger to a particular citizen.

We must concern ourselves with the age distribution of murder victims, for our projections are influenced by it. The breakdown by age of those murdered changed noticeably between 1963 and 1971; the national fraction of victims aged between 20 and 24, for instance, climbed from 11.3% to 16.2%. But the number of Americans in this age category increased so substantially that people in it actually became slightly safer relative to other age ranges. The relevant risk factor for a particular age group L, α_L, is given by:

$$\alpha_L = \frac{\text{fraction of murder victims in age group L}}{\text{fraction of total population in age group L}}$$

The values of α_L in the United States for 11 age groups were calculated for 1963, 1968, and 1971, and are given below with the average for each group.

Table 2: Homicide Risk Factors in the U.S. for Different Age Ranges

Age Range	1963	1968	1971	Average of the three years
(1) 0-14	.21	.16	.16	.18
(2) 15-19	.75	.95	.91	.87
(3) 20-24	1.75	1.88	1.69	1.77
(4) 25-29	2.04	2.06	2.20	2.10
(5) 30-34	2.01	2.04	1.91	1.98
(6) 35-39	1.89	1.85	1.92	1.89
(7) 40-44	1.65	1.67	1.51	1.61
(8) 45-49	1.26	1.27	1.22	1.25
(9) 50-54	1.13	1.03	1.02	1.06
(10) 55-59	.97	.88	.78	.88
(11) 60+	.65	.63	.61	.63

Sources: FBI Crime Reports, U.S. Census Reports, 1960 and 1970

The differences in the factors for any particular age group tend to be rather small, and deviations from the three-year mean are rarely more than a few per cent. Indeed, since the fraction of total murders for a given age group is approximately governed by a binomial random process, the distances from the average can be explained as typical random fluctuations. One does, however, sense a faint shift of risk from the over-40 group to those under 40.

There is some evidence of local deviations from this national pattern. Block and Zimring (5) found notable changes in the age distribution of Chicago murder victims from 1965 to 1970, and associated these changes with an increasing fraction of homicides related to robbery. But unlike variations in the overall growth multipliers we considered earlier, moderate changes in the age dependence of homicide risk have only a second-order effect in the models we will use. (This happens because any increases in relative risk at certain ages are largely compensated for in the expression for homicide probability by the corresponding decreases at other stages of life.) Thus it is sufficient for our purposes to allow the near constancy of the national age distribution for homicide victims to govern our assumptions for the future. The result is:

Assumption 2:

The age distribution of (or risk factor for) victims of murder will remain the same in the future as in recent years, and will be about the same in all cities.

Specifically, this means that the average α_L's for the 11 age groups of Table 2 will be used in projections. Technically, the α_L's cannot remain constant while the age profile of the population changes, for they are bound by the constraint $\sum_{1}^{11} \alpha_L x_L = 1$, where x_L the fraction of citizens in group L. But there is no reason to expect drastic age shifts in the future, especially under the assumption we now make in Assumption 3.

Assumption 3:

The longevity distribution for deaths due to natural causes and accidents continues as at present.

This condition should not be construed as a vote of "no confidence" in science and medicine. It merely expresses the simple notion that an indicator of public safety should not be dependent on progress in areas irrelevant to safety. It adds a touch of conservatism to our estimates, for any increases in life expectancy increase the period in which individuals are exposed to murder risk.

As a final postulate we have:

Assumption 4:

Public policies on homicide-related issues will not change measurably from those of the early 1970's.

We are interested in the natural evolution of murder levels assuming the continuation of the status quo. Nowhere do we wish to imply that future homicide rates cannot be influenced by governmental policies or citizen movements. But is is certainly undesirable for us to attempt to estimate the probability of any particular reform or its efficacy when in force; hence this assumption.

We now have four simple assumptions about future homicide. In the next section, we will use them to build our models.

Projections of Urban Homicide Risk

We now attempt to estimate under several models the quantity P_H, the probability of death by murder for someone born now who lives all his life in a given city. Before we proceed, we must consider two questions concerning mobility which might affect the calculations: (A) To what extent do those out-of-towners who enter the city for various reasons "siphon off" homicide risk from its inhabitants:, and (B) even someone who lives in a city all his life leaves it for some time; to what extent should this absence affect the value of P_H? The statistics indicate that the effect mentioned in (A) is relatively minor; those who enter the cities for work, shopping, or entertainment apparently do so with a high degree of safety. In New York in 1971, for instance, only 7 of the 1466 recorded murders took place in the two police precincts which include, among other things, the entire Wall Street financial district and most of the vast business, shopping and cultural complex on the East Side. The small exaggeration of danger to city residents because of this effect is plausibly balanced by the conservative assumptions we used earlier.

As for (B), it may well be true that our hypothetical individual is sometimes in a safer setting than his home town. But while he is in the city, the absence of other residents reduces the "homicide risk pool," and thus, homicide rates based on the total population underestimate his risk. A randomly-chosen baby will, on the average, be out-of-town an amount of time nearly equal to the population average; thus, the opposing tendencies just mentioned probably largely cancel each other. In sum, it does not

appear that ignoring "mobility effects" measurably weakens our calculations.

In (1) it is shown that the homicide probability P_H for someone born at time t follows

$$P_H = \int_0^\infty r(h,t+h)e^{-\int_0^h [r(s,t+s) + v(s,t+s)]\,ds}\,dh$$

where

$r(x,y)dx$ = probability that someone in the city considered who reaches age x at time y is murdered in the next dx.

$v(x,y)dx$ = probability that someone who reaches age x at time y dies in the next dx for reasons other than homicide.

The decline X_H in life expectancy for this person because of the chance of being murdered satisfies

$$X_H = P_H(L_N - L_H) \qquad (1\text{-}A)$$

where

L_N = normal life expectancy

L_H = life expectancy of murder victim.

Since we are considering only babies born now, we can drop the second variable in the expressions for r and v, yielding the simpler expression

$$P_H = \int_0^\infty r(h)e^{-\int_0^h [r(s) + v(s)]\,ds} .$$

Suppose $r_o(x)$ and $v_o(x)$ are the values of $r(x)$ and $v(x)$, respectively, which prevail now. From Postulate 3, under which natural lifespans and accident rates retain their current distributions, we use $v(x) = v_o(x)$ throughout our calcutions. ($v_o(x)$ for different x ranges is shown in Table 3.) From assumption 1, the overall homicide rates in all 50 cities, when demographically corrected to the present, change by the same multiplicative constant over any time period. Coupled with assumption 2's stipulation that the age distribution of victims is itself unchanging from city to city, this postulate implies that $\lambda(x) \equiv \frac{r(x)}{r_o(x)}$ is the same at any x for all the cities we consider. Since condition 2 says further that the current age breakdown of murder victims will continue to prevail, $\lambda(x)$ is simply the overall growth multiplier we have met earlier, where the next x years is the time period over which the growth occurs. Thus, P_H satisfies

$$P_H = \int_o^\infty \lambda(h) r_o(h) e^{-\int_o^h [\lambda(s) r_o(s) + v_o(s)]\, ds}\, dh \,, \qquad (1)$$

and the only remaining task is the specification of $\lambda(x)$. Such a task, however, is anything but elementary.

We should recognize that our previous work concerned correlations between future homicide levels in different cities and the sharing of total risk among different age groups. But these matters concern the distribution of the total number of murders by age and location, and not what this total number is likely to be. That is the question we must deal with now.

It would be nice for our purposes if we had a simple causal model to explain the recent homicide growth and offer insights about future murder levels. But we have already seen that variations in the recent increases in murder rates in 50 quite different

cities can largely be explained as random fluctuations; this fact in itself suggests that a simple explanation of the current trend might be hard to find. There is, however, one theory that our findings do not contradict--the theory that we have witnessed a phenomenon that is largely demographic in origin, caused by the post-World War II "baby boom." This view is apparently popular among criminologists; The New York Times of January 1, 1972 stated that "the experts who have precisely studied the homicide patterns in the United States over the years say that the real cause for the increase is demographic rather than social." (Underlining added.) The Times quoted one of America's leading criminologists as explaining that "the statistics (are) a reflection of the fact that during the nineteen-forties and early fifties there was a high fertility rate in this country." We proceed now to investigate this hypothesis for, if it is true, we can obtain values for $\lambda(h)$ by using the projections of future birth rates which have been prepared by statisticians and demographers.

The only available information that indicates the age distribution of those who commit murder is the annual FBI homicide arrest data. There are, of course, problems in using this data, because (a) not all murders are solved, (b) arrests are not convictions, and (c) the average number of arrests per murder may vary with age. But we must do the best we can, so we assume that the number of murders committed by members of each age group is proportioned to the number of homicide arrests in that group. We should note, however, that this procedure might exaggerate the impact of demographic changes. Teenage gang members, for example,

Table 3: Instantaneous Death Rate $V_o(x)$ for Age x when Homicide Isn't Cause of Death

Age	$V_o(x)$
0-15	.0024
15-19	.0012
20-24	.0012
25-29	.0015
30-34	.0016
35-39	.0022
40-44	.0036
45-49	.0058
50-54	.0090
55-59	.0134
60+	.0526

Source: Vital Statistics of the United States, 1967. (Corrections were made to "weed out" the effect of homicide.)

There is, in fact, considerable variation of $V_o(x)$ with x in both the 0-15 and 60+ ranges, but these variations are not very important for our purposes. x is, of course, measured in years.

may all be charged with one murder; this raises the arrest rate of that age group relative to older groups in which gang operations are rare.

For the year 1964, we get the following breakdown of murder arrest rates:

Table 4: Murder Arrest Rates In the United States, 1964

Age Group	No. of arrests per million persons
0-15	1.6
15-19	55.0
20-24	89.6
25-29	95.2
30-34	79.0
35-39	60.0
40-44	47.6
45-49	35.8
50-54	35.0
55-59	16.6
60+	9.1

Sources: FBI Uniform Crime Reports, 1964.
United States Census, 1960 and 1970.

Using this table as an index of murder commission rates, we indeed obtain an increase in the national homicide rate when the 1964 age distribution is replaced by that of 1972. But the amount of this increase is slightly under 8%, even if we take note of the slight alteration of the national ethnic composition and the differing changes in age distribution for different ethnic groups, the projected rise changes very little. Thus, less than one-tenth of the actual rise in the national homicide rate since the 1960's can be explained by demographic changes. Under these circumstances, the identification of demography as the "real cause" of the great rise in murder is somewhat bewildering.

Thus, we cannot, it would seem, tie our projections closely to future birth rates. There is great controversy about the origins of the current situation and, as noted earlier, our results about uniform growth of anything make the job of finding quantitative causal models of the problem even more hopeless. (To be sure, even the availability of such causal models would not necessarily make projections more accurate; if homicide were closely correlated, for instance, with unemployment rates, then the prediction of future murder levels would involve the hapless task of predicting the health of the economy over most of the next century.) Thus, we are forced to proceed without clearly understanding the roots of the recent trend. In such a situation, certain approaches would seem prudent; specifically,

1) Instead of one, we should propose several models which cover, roughly speaking, the range of homicide levels we might reasonably expect.

2) The models should be simple and straight-forward. They should not be intricate and elaborate and thus, by their very complexity, create a false atmosphere of exactitude.

3) The results we obtain by using these models must be regarded as highly speculative. (Although not for that reason invalid.)

In the next section, we complete our work by proposing and employing four different projections for the values of $\lambda(h)$.

Projections of Urban Homicide Risk

We consider four models for $\lambda(h)$; they get progressively more pessimistic. For each model, we calculate from equation (1) the values of P_H and X_H for each of the 50 cities mentioned earlier. $r_o(h)$ is estimated from the 1971-72 average homicide rates in Table 1 and the age-distribution factors of Table 2. This is the latest complete data available. $v_o(h)$ is estimated from Table 3. We note that the continuous variation of $r_o(h)$ and $v_o(h)$ with h which equation (1) allows cannot be implemented in practice, but this is only a minor source of inaccuracy.*

I The Pangloss Model

This model is named after Dr. Pangloss, the relentless optimist in Voltaire's *Candide*. It proceeds on the assumption that the murder rise since the mid 1960's is an aberration, and that homicide levels will soon return to those of the late 50's and early 60's, the lowest in the past half century. Specifically, the Pangloss model assumes that $\lambda(h) = \frac{1}{2}\left(1 + e^{-\frac{h}{7}}\right)$, under which the return to lower levels will be about 90% completed in 15 years when today's babies enter the higher-risk age brackets. Realistically speaking, this is about the most optimistic projection of future murder rates that one can make now.

II The Current Rates Model

This model uses $\lambda(h) = 1$, and thus, simply projects the current pattern throughout the future. Many people will consider

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*We are of course ignoring random fluctuations in future murder levels. It can easily be shown that random effects are totally negligible to first order.

this model the most useful for understanding the homicide problem as it exists now. Others might find it unsatisfactory in the absence of reasons that homicide should stabilize at current levels, much as a statistician might dislike using a uniform prior in Bayes' Theorem when he sees no reason that the underlying distribution is anywhere near uniform.

III The Saturation Model

The annual homicide rate in the U.S. since 1962 is given in Table 5 below.

Table 5: American Homicide Rate 1962-73
(Murders per 100,000 inhabitants per year)

Year	Rate
1962	4.7
1963	4.5
1964	4.9
1965	5.1
1966	5.6
1967	6.1
1968	6.8
1969	7.3
1970	7.8
1971	8.5
1972	8.9
1973*	9.3

*The 1973 figure is an estimate, based on the fact that murder increased by 5% over 1972 for the first 9 months of the year. Given the corresponding increase of almost 1%in the U.S. population, the murder rate went up by just about .4 to the nearest tenth.

The average murder rate for 1962-63 is 4.6, which is approximately the base level which prevailed from about 1956 to 1963. It is reasonable to assume that the current period of increase began in 1964. For the first two years the national rate rose at an average speed of .25 per year; the pace of increase then quickened sharply and averaged .57 per year from 1965-71. In both 1972 and 1973, the annual rate of growth fell to .4. Conceivably the 1972 figure is an artifact associated with the large jump in the murder rate in 1971. But it is not clear that this is so, for even with the large 1971 increase, the average rise for 1969-71 was .57, exactly the same as that for 1966-68.

It is relevant to consider at this point a function y(t) which satisfies a "saturation" differential equation of the form:

$$\frac{dy}{dt} = K(B - y)(y - A) \quad , \qquad (2)$$

where $K > 0$, $B > A$ and y is slightly above A at the beginning of the process. The time derivative of y is of course quadratic in y; it is very close to zero near both A and B and reaches its maximum at $\frac{A + B}{2}$. It is interesting to note that $\frac{dy}{dt}$ is nearly constant for a fairly large range around $\frac{A + B}{2}$, attaining values over 90% of its maximum for y values from approximately $\frac{2A + B}{3}$ to $\frac{A + 2B}{3}$ (which is 1/3 of the distance from A to B). Thus, y will begin its increase from near A quite slowly; then it accelerates for a while but soon reaches nearly linear growth in time. The growth rate tapers off as B gets relatively close, and the function spends the rest of its days in an asymptotic approach to the value B.

Qualitatively at least, the national homicide rate since 1963 has behaved pretty much like the solution of a saturation equation, with its initially slow rate of increase, followed by a period of approximately linear increase and then a slackening of growth. This suggests the desirability of a saturation model for $\lambda(h)$, especially since the notion of a ceiling on homicide growth has intuitive appeal. If we interpret $y(t)$ as the overall homicide rate in America, and choose $A = 4.6$ as the floor level near which the current rise started, (2) becomes

$$\frac{dy}{dt} = K(B - y)(y - 4.6) .$$

We set the initial condition $y(o) = 4.9$ from the 1964 data. (We need not assume a discontinuous jump from the stable level 4.6; conceivably a small perturbation started the increase earlier but it was obscured by random fluctuations.) Then $y(t)$ follows

$$y(t) = \frac{4.6(B - 4.9) + .3Be^{+K(B - 4.6)t}}{B - 4.9 + .3e^{K(B - 4.6)t}} \qquad (3)$$

The parameters B and K should be chosen to get the best fit the actual homicide levels for 1965 on. Using a least-squares criterion and t measured in years, the best parameter values are $B = 9.75$ and $K = .11$ (to the nearest .05 and .01, respectively). For these values in (3), we get the following predicted murder rates for 1965-73:

Table 6: Predicted Homicide Levels from Saturation Curve, 1965-1973

Year	Predicted Murder Rate	Deviation From Actual Rate
1965	5.11	.01
1966	5.43	-.17
1967	5.91	-.19
1968	6.52	-.28
1969	7.24	-.06
1970	7.94	.14
1971	8.54	.04
1972	8.99	.09
1973	9.29	-.01

It should be mentioned that this saturation curve does a slightly better job in fitting the data from 1963 on than the best least squares straight-line fit to that data. Since the 1971-72 average murder rate was 8.7, we obtain the ratio $\lambda(h)$ from the relationship $\lambda(h) = \frac{y(h + 7.5)}{8.7}$. (The 7.5 arises since $t = o$ in the y equation was the middle of 1964.) Hence $\lambda(h)$ in this model satisfies

$$\lambda(h) = \frac{22.31 + 2.93e^{.57(h + 7.5)}}{42.20 + 2.61e^{.57(h + 7.5)}} .$$

We should note, of course, that the predicted saturation level of about 9.8 is only about 12% above the 1971-72 murder rate and only 5% above the 1973 rate. This model has the curious property that, by the time it appears in print, it may already have been proved wrong.

IV The Linear-Growth Model

Our last model considers a grim possibility that we can by no means exclude. Perhaps the murder rate in American will not stabilize or decline, but will simply keep growing. The evidence to the contrary cited in the previous model is, after all, very limited, and might well be a "mirage" created by two years of downward random fluctuations. And the national murder rate declined for several consecutive decades until the late 1950's, suggesting that homicide cycles, if they exist, are somewhat longer than rain cycles. Several simple growth models come to mind: the rate could grow by a fixed percentage each year, or it could grow with ever-increasing speed, following an equation of the form $\frac{dy}{dt} = Ky^{\alpha}$ where $\alpha > 1$. (The last formulation allows for the bizarre possibility that the entire population will have been murdered in a finite amount of time.) The available data makes a fixed absolute increase per year more plausible than the more ominous growth patterns. Thus, we use a linear-growth hypothesis of the form $\lambda(h) = 1 + \alpha h$. We choose $\alpha = .04$ since this value best approximates the very recent pattern. But it should be emphasized that linear growth is hardly the most pessimistic model reasonably consistent with recent patterns, and it would be inappropriate to regard the consequences of this model as upper bounds on the quantities calculated.

The calculations for all the models are presented in Table 6. For ease of comprehension, P_H values are expressed in the form 1 in X; the top number for a given city under a given model is the value of X for that city in that model. The bottom number is the associated decline in life expectancy (in years) because of murder.

Table 7: Homicide-Risk Indices in the 50 Largest American Cities Under Four Projections of Murder Levels

City	Rank	Pangloss Model	Current Rates Model	Saturation Model	Linear Growth Model
New York	19	131	67	60	27
		.3	.5	.6	1.3
Chicago	18	117	60	54	24
		.3	.6	.6	1.5
Los Angeles	24	161	82	74	33
		.2	.4	.5	1.1
Philadelphia	17	122	62	56	25
		.3	.6	.6	1.4
Detroit	2	69	35	32	14
		.5	1.0	1.1	2.5
Houston	12	110	56	50	23
		.3	.6	.7	1.6
Baltimore	5	74	38	34	15
		.5	.9	1.0	2.3
Dallas	11	107	55	50	22
		.3	.6	.7	1.6
D. C.	6	78	40	36	16
		.5	.9	1.0	2.2
Cleveland	3	69	35	32	14
		.5	1.0	1.1	2.4
Milwaukee	42	353	179	161	71
		.1	.2	.2	.5
San Francisco	29	208	106	96	42
		.2	.3	.4	.8

City	Rank	Pangloss	Current Rates	Saturation	Linear Growth
San Antonio	26	174	89	80	35
		.2	.4	.4	1.0
San Diego	48	544	276	248	110
		.1	.1	.1	.3
Boston	22	155	79	71	32
		.2	.4	.5	1.1
Memphis	20	153	78	70	31
		.2	.5	.5	1.1
St. Louis	7	78	40	36	16
		.4	.9	1.0	2.2
New Orleans	13	113	58	52	23
		.3	.6	.7	1.5
Phoenix	34	230	117	105	47
		.2	.3	.3	.7
Columbus	33	224	114	103	46
		.2	.3	.3	.8
Seattle	41	335	170	151	67
		.1	.2	.2	.5
Pittsburgh	35	243	123	111	49
		.2	.3	.3	.7
Denver	23	160	81	73	33
		.2	.4	.5	1.1
Kansas City	21	155	79	71	32
		.2	.4	.5	1.1
Atlanta	1	55	28	25	11
		.6	1.2	1.4	3.1

City	Rank	Pangloss	Current Rates	Saturation	Linear Growth
Buffalo	27	178	91	82	36
		.2	.4	.4	1.0
Cincinnati	25	161	82	74	33
		.2	.4	.5	1.1
San Jose	49	550	279	251	111
		.1	.1	.1	.3
Minneapolis	39	311	158	142	63
		.1	.2	.2	.6
Ft. Worth	10	104	53	47	21
		.3	.7	.7	1.6
Toledo	40	324	165	147	66
		.1	.2	.2	.5
Newark	4	73	37	33	15
		.5	.9	1.0	2.3
Portland(Or.)	44	389	198	178	79
		.1	.2	.2	.4
Oklahoma City	32	222	113	102	45
		.2	.3	.3	.8
Louisville	15	117	60	54	24
		.3	.6	.6	1.5
Oakland	14	115	59	53	24
		.3	.6	.7	1.5
Long Beach	31	222	113	102	45
		.2	.3	.3	.8
Omaha	43	384	195	175	78
		.1	.2	.2	.5

City	Rank	Pangloss	Current Rates	Saturation	Linear Growth
Miami	8	100	51	46	21
		.4	.7	.8	1.7
Tulsa	37	274	139	125	56
		.1	.3	.3	.6
Honolulu	38	274	139	125	56
		.1	.3	.3	.6
El Paso	50	634	322	289	128
		.1	.1	.1	.3
St. Paul	46	457	232	209	92
		.1	.2	.2	.4
Norfolk	28	205	104	94	42
		.2	.3	.4	.8
Birmingham	9	101	52	46	21
		.4	.7	.7	1.7
Rochester	36	262	133	120	53
		.1	.3	.3	.7
Tampa	18	128	65	58	26
		.3	.5	.6	1.3
Wichita	47	474	241	216	96
		.1	.1	.2	.4
Akron	30	212	108	97	43
		.2	.3	.4	.8
Tucson	45	451	229	206	91
		.1	.2	.2	.4

Thus, the table indicates, for example, that under the Current Rates model, the homicide probability for a baby born now in New York is 1 in 67 and its life expectancy is cut by 1/2 year by the amount of murder in that city.

There is no need for a great deal of discussion of these results; the numbers speak loudly for themselves. It is interesting that the projected homicide probability in the safest city under the most optimistic model is 1 in 634; a rather crude survey suggests that many people in Boston and New York think that P_H at current rates is .001 or less. (Indeed, a police official associated with crime analysis in a large American city did not consider .001 an unreasonable estimate for P_H in one of the most dangerous parts of that city.) At current murder levels, a randomly-chosen baby born in a large American city has almost a 2% chance of dying by homicide; among males, the figure is 3%. Thus, an American boy born in 1974 is more likely to die by murder than an American soldier in World War II was to die in combat. With the reduction in auto fatalities because of lower speed limits and new safety devices, it is plausible that murder might soon surpass auto accidents as a cause of death in America. The projections under the linear-growth model reach astonishing levels, with P_H values up to 1 in 12 and life expectancies diminished by more than 3 years. It would of course be pleasant to dismiss such results as Cassandra-like ravings, but the facts will not cooperate. The murder rate in some sections of some cities are already very close to the maximum levels predicted in the linear-growth formulation. And in 1916, the homicide rate for all of Memphis was 90 per 100,000 (2), indicating that levels much higher than today's are hardly out of the question. All in all, there is very little encouraging in these projections.

The numbers calculated indicate the average homicide risk in each city. It should be stressed that these mean risk levels are themselves weighted averages of the risks borne by different elements of the population, and that these risks vary greatly with such factors as sex and race. The New York Times [4] found, for instance, that blacks in New York are murdered at eight times the rate of whites and males at four times the rate of females; thus--assuming no race-sex correlation--a black male born there has a murder probability roughly 32 times that of a white female. The median murder risk is in some cities as low as half the mean levels given in the calculations. Indeed, in the same way that the center-of-mass of a doughnut is at the center of the hole, it is conceivable that very few individuals face exactly the risk levels shown in the tables. But to say this is not to suggest that the "macroscopic" picture provided here is unimportant. Much research effort has gone into estimating the variance of homicide risk among different groups of citizens, but it appears that almost no effort has been expended in finding the mean danger level around which this variation takes place. An attempt to estimate this mean value carefully is particularly appropriate because it is apparently much higher than is widely believed.

Conclusions

We have tried to obtain some reasonable indicators of the extent of homicide in American cities. In the course of the work we studied recent trends in murder in some detail.

We used the information we gained to make several projections for the probability of death by murder and the corresponding decrease in life expectancy for a baby born now in each of 50 American cities.

The predictions, as we have seen, imply that murder in our urban centers is not nearly as rare as we might have thought. But it is important to remember that our forecasts were explicitly tied to the assumption that no changes in public policy or citizen response towards homicide will be forthcoming. There is no reason that this need be so. Perhaps the best way to invalidate the grim predictions in this paper is to invalidate the premise of public inaction on which they were based.

Appendix A

Estimating the Effects of Randomness in the 50 Magnification Ratios Under a Uniform Growth Postulate

Suppose the parameter by which homicides were generated in 1963 and 1965 in a certain city was ω. (i.e. the actual murder toll was spawned from the distribution $N(\omega,\omega)$.) Let the corresponding parameter for 1971-72 be β. Then if N_1 was the city's average population* over the earlier period, N_2 its average population* in 1971-72 and k its demographic correction factor for the latter interval, its observed magnification ratio was one sample value of the random variable s where s follows

$$s = \frac{\frac{kx}{N_2}}{\frac{y}{N_1}} = \frac{\alpha x}{y}$$

where x is $N(\beta,\beta)$, y is $N(\omega,\omega)$, $\alpha = \frac{kN_1}{N_2}$. Equivalently, $s = z/y$ where z is $N(\alpha\beta,\alpha^2\beta)$. Now we make our uniform growth hypothesis: suppose that, in each of the 50 cities, the expected value of the adjusted homicide rate (kx/N_2) for 1971-72 is 1.92 times that for 1963 and 65. (i.e. $k\beta/N_2 = 1.92\omega/N_1$ or $\alpha\beta = 1.92\omega$) This postulate is based on the fact that the median of the growth ratios, which is given by $\alpha E(x)/E(y)$, is 1.92. (The median is more appropriate than the mean in this situation for reasons to be indicated shortly.) Now the random variate z is $N(1.92\omega, 1.92\alpha\omega)$; what we want to know is

*Actually, homicide rates were calculated separately for each of the four years considered so N_1 and N_2 are effective averages.

how far s might deviate from its median value. More precisely, if s_j is the variable s for city j $(j=1,\ldots,50)$, we need information about the anticipated behavior of the set of s_j's, which are presumed independent though not, of course, identically distributed. We are (loosely speaking) testing the hypothesis that a uniform national trend produced the changes in homicide rates listed in Table 1.

We note that, from the properties of normal variates, s_j can be written in the form:

$$s_j = \frac{1.92\omega_j + \sqrt{1.92\alpha_j\omega_j}\; r_j}{\omega_j + \sqrt{\omega_j}\; q_j} = \frac{1.92\sqrt{\omega_j} + \sqrt{1.92\alpha_j}\; r_j}{\sqrt{\omega_j} + q_j}$$

where $\alpha_j = kN_1/N_2$ for city j.

ω_j = the mean of the a priori distribution of the number of murders in 1963 and 65 in city j.

r_j and q_j are two independent unit normal variates.

We do not, of course, know what ω_j was; all we have is the number of homicides that really took place. One way of proceeding would involve using Bayes' Theorem with, perhaps, a uniform prior, to obtain a distribution for ω_j, and then using that information to get the distribution of the number of killings in 1971-72 and hence the distribution of s_j under the uniform growth hypothesis. Another somewhat simpler way utilizes some properties of the data itself. We do, after all, have 50 different murder totals for the period considered, and the density of observations increases as the numbers themselves get smaller. (and percentage deviations of sample values from their underlying means get larger.) Thus it is not overly unreasonable to assume, as a first approximation, that the actual distribution of ω_j's is about the same as the observed distribution of murder totals. And the individual values of population and demographic corrections α_j are heavily concentrated between .9 and 1, with .9 about the 20th percentile of these values. We might, therefore, use the estimate $\alpha_j = .9$ for all 50 cities, because (a) deviations from this value are relatively unimportant for our calculations, which use $\sqrt{\alpha_j}$ and (b) the use of a low estimate for α_j tends to give conservative estimates of the variation, and in this way compensates for the uncertainty associated with interpolation from census data, etc.

We will go ahead with the second method mentioned above, ($\alpha_j = .9$, distribution of W_j's is sample distribution) subject to one modification. Since each s_j is the ratio of two normal variates, it has infinite mean and variance. This does not invalidate the model for homicide generation, for it corresponds to the fact that the probability of no murders at all in the earlier period, while very small, is nonetheless nonzero. But it does indicate how our statistical tests might be distorted because of wildly improbable events which, among other things, clearly did not occur. We thus make an alteration for the top and bottom 1% tail of each of the 100 unit normal variates we encounter. A unit normal variable exceeds 2.33 with probability .01; given that it exceeds 2.33, its average value is 2.7. We replace the tail of each of the variables beyond 2.33 with the fixed point 2.7 which is assigned probability .01, and proceed in an analogous way at the lower 1% tail. This procedure allows us to estimate reasonably the two or so measurements we would

expect to be spawned by the "outer hundredths" while it affects not at all the numbers which arise from more typical sample values.

We have, in summary, 50 independent variables s_j of the form

$$s_j = \frac{1.92\sqrt{\omega_{jo}} + 1.32\, r_{jo}}{\sqrt{\omega_{jo}} + q_{jo}}$$

where ω_{jo} = the actual homicide total for 1963+65 in city j.

r_{jo} and q_{jo} are unit normal variates except for the "truncation" in the outer one-percentiles.

The 1.32 arises because of the approximation $\alpha = .9$. All the variates have median 1.92; their means, under our assumptions, vary slightly and exceed the median by a few-hundredths. (Interestingly, the mean of the observed s_j's was .09 larger than the median, about what we would expect.) It is important to remember that s_j is NOT necessarily meant to represent the murder growth factor for city j; the use of ω_{jo} follows our assumption that the actual distribution of parameters ω_j is the observed distribution of the number of murders. We are interested primarily in the behavior of the 50 random variables as a group, and quite secondarily in the interpretation of any particular variate.

We will not try any one statistical test, but will instead compare some characteristics of the group of actual magnification factors with those for the group generated by the set of random variables. While there is no reason to belabor the details, a short discussion of the methods used to handle the 50 random variables is appropriate.

The calculations, while not sufficiently interesting to warrant detailed description, are in fact less arduous than one might think. To find the expected value of t, defined as $\max(s_1,\ldots,s_{50})$, we do not really need to evaluate 50-fold integrals. All the variates have the same median and nearly the same mean; under our assumptions thus the largest measurement is likely to be among those variables with the highest variance. (i.e., the lowest values of ω_j) As a first approximation to E(t), we might find E(u), where u is the largest of the measurements generated by the h lowest ω_j values. A second estimate would consider the event that v, the largest of the s_j's from the next h lowest ω_j's exceeds u; the associated correction of the estimate for E(t) is E(max(0,v-u)). We choose h relatively small (about 6) so that dealing with u and v is manageable, and we note with pleasure that the correction terms approach zero with admirable speed, meaning we can stop correcting fairly soon. Other calculations can likewise be simplified. The results of the investigation are presented in the main text.

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