Crime-Related Secondary Effects of Sexually-Oriented Businesses:

Report to the City Attorney

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I am a Professor at the University of California, Irvine with appointments in the Departments of Criminology, Environmental Health Science, and Planning. My *curriculum vitae* is attached to this report. My degrees include a B.S. from the University of Wisconsin and an M.A. and Ph.D. from Northwestern University. I have taught graduate courses in statistics and criminology at the University of California, Irvine; the University of Minnesota; the University of Michigan; the University of New Mexico; Arizona State University; the State University of New York, Albany; and the University of Illinois, Chicago. I have supervised more than two-dozen doctoral students in statistics and/or criminology at these universities. My students hold appointments at major research universities in the U.S. and U.K.

My training and experience qualify me as an expert in criminology and statistics. I joined the American Society for Criminology and the American Statistical Association in 1977 and am currently a member of both scholarly societies. My scholarly contributions in these fields have been recognized by awards from Federal and state government agencies and scholarly societies. As an expert in these fields, I have served on Federal and state government task forces and panels and have served on the editorial boards of national peer-reviewed journals. I am the author or co-author of five books more than 70 articles in these fields.

Throughout my career, I have applied my expertise in statistics and criminology to the problem of measuring site-specific public safety hazards, especially the hazards associated with sexually-oriented businesses (SOBs). These hazards are also called "ambient crime risks" or "crime-related secondary effects." I have advised local, county, and state governments on these problems for nearly 30 years. I have been deposed or testified in fifteen cases in the last four years.

The City of Los Angeles has asked me to review the facts and materials in this suit[1] and to express opinions on certain issues. Based on my background and research, I have three general opinions:

> **Opinion 1**: The criminological theory of ambient crime risk, known as the "routine activity theory," predicts that SOBs have large, significant crime-related secondary effects. The effect is the product of three factors. (1) SOBs draw patrons from wide catchment areas. (2) Because they are disproportionately male, open to vice overtures, reluctant to report victimizations to the police, *etc.*, SOB patrons are "soft" targets. (3) The high density of "soft" targets at the site attracts predatory criminals, including vice purveyors who dabble in crime and criminals who pose as vice purveyor in order to lure or lull potential victims.
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> **Opinion 2**: In the last thirty years, empirical studies employing a wide range of quasi-experimental designs have found that SOBs have large, significant crime-related secondary effects.

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[1] *Alameda Books v. City of Los Angeles*. U.S. District Court, Central District of California, Case No. CV 95-7771

> **Opinion 3**: Given that strong criminological theory predicts the effect, and given that the prediction is corroborated consistently by the empirical literature, it is a *scientific fact* that SOBs pose ambient crime risks.

In addition to these three general opinions, I have three opinions that are specific to *Alameda Books*.

> **Opinion 4**: Since the theoretical risk factors specified in my first opinion are common to all SOB subclasses, all are expected to pose ambient public safety hazards. The qualitative nature of the hazard may vary by subclass nevertheless. This will occur when the defining characteristic of a subclass creates opportunities for a particular type of crime; or when the characteristic interferes with routine policing strategies.

> **Opinion 5**: In this suit, the two relevant subclasses are SOBs that sell video tapes and DVDs for off-site viewing (hereafter, "stand-alone bookstores" or "bookstores") and SOBs that sell video tapes and DVDs for off-site viewing while, also, providing private or semi-private booths for on-site viewing of video tapes and DVDs (hereafter, "combined bookstore-arcade" or "bookstore-arcade"). Although both subclasses have large, significant crime-related secondary effects, there are salient qualitative differences. Compared to stand-alone bookstores, *e.g.*, combined bookstore-arcades pose higher risks for crime. Geo-coded crime incident data for the neighborhoods around 19 Los Angeles SOBs corroborate this theoretical expectation.

> **Opinion 6**: Poisson regression analyses of crime incidents in the vicinity of 19 Los Angeles SOBs demonstrate a significant relationship between ambient crime victimization risk and distance from the site. Victimization risk at the site of a combined bookstore-arcade is more than double the risk at the site of a stand-alone bookstore. For both subclasses, victimization risk diminishes rapidly with distance until, at approximately 900 feet, the risks are roughly equal for the two subclasses. In general, victimization risk for bookstore-arcades is more densely concentrated in the immediate vicinity of the site.

My report begins with a necessary introduction to the concept of ambient crime risk. The fundamental question in this suit is whether combined SOBs pose lower ambient risks than stand-alone SOBs. Based on my analyses, the answer is, Yes. Readers who are familiar with implicit concepts can skip directly to the results of my analyses in Section 3 below. But most readers will benefit from the following introduction.

1. AMBIENT CRIME RISK

Crime "risk" is a novel concept to most readers. To the individual, crime *risk* is synonymous with the annual crime *rates* reported in the news media. To illustrate, in 2000, the per capita robbery rates for Los Angeles and San Diego were 0.0041 and 0.0014. For purely aesthetic reasons, newspapers report these rates as whole numbers per 1,000 residents. So the Los Angeles and San Diego rates could be expressed identically as 4.1 and 1.4 robberies per 1,000 residents per year. Since *per capita* rates have practical advantages, however, that metric is preferred.

In either the *per capita* or per 1,000 metric, Los Angeles is nearly three times *riskier* than San Diego. The risk ratio statistic makes this point:

$$\text{Risk Ratio} = 0.0041 / 0.0014 \approx 2.93$$

A tourist who spends a week in Los Angeles and a week in San Diego is three times more likely to be robbed in Los Angeles. In either city, of course, the risk is exceedingly low. This point is made clear by the waiting time statistic. In San Diego, a hypothetical average tourist will spend more than 714 years waiting to be robbed:

$$\text{Waiting Time} = 1 / 0.0014 \approx 714.3 \text{ years}$$

In Los Angeles, on the other hand, the wait is only 244 years:

$$\text{Waiting Time} = 1 / 0.0041 \approx 243.9 \text{ years}$$

The waiting time statistic illustrates one practical advantage of *per capita* rates; the average waiting time is the inverse of the *per capita* rate. This relationship depends on simple Poisson assumptions that will be developed at a later point in this report. For now, I will say only that these assumptions may not hold exactly for inter-city comparisons, so these waiting times are rough approximations.

Intra-city heterogeneity complicates the *per capita* crime rate analogy. Put simply, “bad” neighborhoods in low-risk cities are more dangerous to the hypothetical tourist than “good” neighborhoods in high-risk cities. Temporal heterogeneity presents another complication. Since the hypothetical tourist cannot be in two places at the same time, inter-city risk comparisons require imagination. At the smaller geographical scales that are relevant to this suit, however, the effects of both complications vanish. Given a reasonably small area – say, a few city blocks – a simple ambient crime rate captures all the essential features of crime risk.

To define the *ambient* crime rate, divide the area of a city into a large sample of parcels. The division algorithm can be wholly arbitrary or haphazard. The parcels can be trapezoids, squares, circles, or any irregular shape. No two parcels must have the same shape. The only requirement is that each have a calculable surface area. Following the division, wait a fixed period – say, one year – and count the number of crimes that occurred in each of the parcels. If CRIME_d denotes the number of crimes that occurred in the d^{th} parcel, then the ambient crime rate for the d^{th} parcel is

$$\text{RATE}_d = \text{CRIME}_d / \text{AREA}_d$$

where AREA_d is the surface area of the d^{th} parcel. RATE_d is a property of the d^{th} parcel. Unlike the *per capita* crime rates that we read about in newspapers, this ambient rate has no inevitable consequences for individuals. If RATE_d is particularly high, individuals can avoid the risk by avoiding the d^{th} parcel (and other "bad" neighborhoods).

Figure 1a Here

When ambient risk emanates from a point-source, a sensible division algorithm results in a set of concentric circular parcels as shown in Figure 1a. Noise is a good model of ambient crime risk in many respects. Noise emanates from its point-source in all directions, for instance, and decays rapidly with distance. So does ambient crime risk when it emanates from a source such as, in this instance, an SOB. Like noise, ambient crime risk emanates in all directions and diminishes with distance from the point-source. In the real-word, of course, the orderly emanation process will be distorted by buildings, walls, and other obstacles. If we have a reasonably large sample of point-sources, however, the effects of these obstacles will "average out," revealing the expected ambient risk pattern.

Figure 1b Here

Figure 1b illustrates this point for a sample of 19 Los Angeles SOBs. The horizontal axis in Figure 1b is calibrated in 50-foot increments from 50 to 1,100 feet from the SOB address, yielding concentric circular parcels with radii of 50, 100, 150, ..., 1,100 feet. The area of the d^{th} concentric circle is

$$\text{AREA}_d = \pi\,(50d)^2 - \pi\,[50(d-1)]^2 \quad \text{for} \quad d = 1, 2, 3, \ldots$$

The vertical axis in Figure 1b plots the ambient victimization rate for personal crimes such as homicide, robbery, assault, and so forth.

The ambient risk function in Figure 1b is the mean (or *average*) ambient risk for 19 Los Angeles SOBs. *On average*, these SOBs are the point-sources of ambient crime risk. The ambient risk decays rapidly with distance from the SOB address. Walking toward the address, the hypothetical pedestrian is confronted with exponentially increasing risk; walking away from the address, on the other hand, risk decays.

Figure 1c Here

Figure 1c plots the same function as a *risk ratio*. To facilitate interpretation, these risk ratios are standardized by the mean ambient rate of the entire 1,100-foot circle. Standing within 50-feet of an SOB, the hypothetical pedestrian's victimization risk is approximately eleven times higher than the neighborhood average. At 300 feet, ambient victimization risk is "only" twice the neighborhood average. After 750 to 850 feet, the difference between the point-source and neighborhood background risks is practically imperceptible. This is not to say that the point-source risk is zero (or that it does not exist); but it is difficult to measure at that distance. It is like noise in that respect.

2. THE LOS ANGELES DATA

To address the central questions of this suit, data were collected from the City's Department of Building and Safety and from the LAPD. Site visits and interviews were conducted to assess the properties and quality of these data.

2.1 THE STUDY SITE SAMPLE

Selecting a sample of SOB sites involves balancing three considerations. First, for purely statistical reasons, the sample should be as *large* as possible; more sites means greater statistical power. Second, for the same reason, the sample sites should be as *homogeneous* as possible; extraneous dissimilarities among the sampled sites reduces statistical power. Third, the history of each sampled site must be well characterized. We must know how long each SOB has been operating, *i.e.*, what subclass it belongs to, and so forth.

Table 2.1 Here

The sample of 20 SOBs listed in Table 2.1 reflects a careful balance of the three considerations. Because the list was compiled by the City's Department of Building and Safety, the history of each site is known. Since the list is limited to stand-alone bookstores and combined bookstore-arcades, it consists of two homogeneous sub-samples. Finally, compared to my experience in other studies, this is a relatively large sample. Although "more data" is always preferred to "less data," the sample proved sufficiently large.

Between April, 2006 and the present, the suitability of each of the 20 sites was assessed. The assessment included internet searches and telephone inquiries in many instances and "eyeball" site visits in every instance. This process led to the exclusion of the site (in green) located at 6315½ Hollywood Boulevard because it was located within a few feet of a live-entertainment SOB. Keeping this site in the sample would have introduced an unnecessary element of heterogeneity. Excluding this site left seven stand-alone bookstores (in blue) and twelve combined bookstore-arcades (in red).

2.2 THE CRIME INCIDENT SAMPLE

Selecting a sample of crime incidents involves an analogous balancing process. The sample should be as large as possible, *e.g.*, but yet optimally homogeneous, reliable, and interpretable. Each crime incident has several bits of information, including the type of crime, the location, the time of occurrence, and so forth. Since the location of the incident was the most important bit of information, given our study goals, we began (and ended) our search for data at the LAPD's COMPSTAT unit.[2]

The architecture of the COMPSTAT database supports retrieval of crime incidents by LAPD Reporting Districts. To ensure the completeness of our data, we requested geo-coded crime incident reports for every Reporting District that was located within 1,500 feet of any of the 20 SOBs, beginning January 1, 2001. To comply with an existing policy, COMPSTAT excluded all information on rape cases and stripped unique internal identifiers from each incident record. The unique case identifiers were saved in a separate linkable file held by COMPSTAT.

The COMPSTAT file was initially processed with ARCMap 9.0. COMPSTAT latitudes and longitudes were converted to State Plane 9 foot-unit Cartesian co-ordinates. Euclidean distances from crime incidents to SOB sites were computed by the Pythagorean formula. Exploratory analyses suggested that errors in the Euclidean distances were smaller than ten percent. Accordingly, for each site, incidents with distances greater than 1,100 feet were discarded, leaving all incidents in an 1,100-radius of the sites.

The COMPSTAT files described each crime incident with one or more non-exclusive labels drawn from a set of 155. To facilitate analysis, the 155 categories were collapsed into five categories:

UCR Part I Personal (Homicide, Aggravated Assault, Robbery, and Rape)
UCR Part I Property (Burglary, Larceny, Auto Theft, and Arson)
UCR Part II Personal
UCR Part II Property
All Other Incidents

An FBI NIBRS-UCR translation protocol was used to construct the five categories. The translation map and frequency distributions are listed in an appendix. Table 2.2 reports incident totals and subclass means for the five crime categories for each of the 19 sites. Across all sites, the residual "other" category constitutes less than 13 percent of the incidents.

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[2] Headed by Detective Jeff Gowdown, the COMPSTAT statistical analysis unit collects and disseminates geo-coded crime incidents for planning and budgeting.

Table 2.2 Here

2.3 CONCLUDING NOTE ON THE SAMPLES

Sites and incidents were excluded from the analytic sample strictly on methodological grounds, usually relating to "missing" data. Incidents involving forcible rape are the exception. These incidents were withheld from us in order to comply with an existing LAPD policy. These exclusions appear to have no substantive impact on the results. To confirm this point, models were replicated with and without excluded sites and crime categories. None of these replications produced results that would be inconsistent with or that would lead me to doubt the reported results.

3. STATISTICAL RESULTS

To address the central questions in this suit, I conducted a statistical analysis based on the Poisson family of models. The analysis compared the ambient crime risk functions of bookstore-arcades to the ambient risk functions of stand-alone bookstores. The results of this analysis demonstrate that the two SOB subtypes have significantly different patterns of ambient risk. Whereas the ambient crime risk of bookstore-arcades is heavily concentrated near the address, the ambient risk of at stand-alone bookstores is more pervasive. From a theoretical perspective, these differences point to qualitatively different policing strategies. The differences legitimate the view that, compared to stand-alone SOBs, the ambient crime risk for combined SOBs is considerably higher and more serious at the source.

3.1 CRIME AS A POISSON PROCESS

In the early 19th Century, French mathematician, S.D. Poisson developed an interest in the scattered distribution of crimes across Paris neighborhoods.[3] Poisson proposed the probability density function that bears his name to describe the spatial scattering of crime incidents.[4] Briefly, if x is the number of crimes that occur in a neighborhood (or any other fixed area) during a year (or any other fixed period of time), the probability that exactly k crimes will occur in the

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[3] Published in 1837 as *Recherches sur la probabilité des jugements en matière criminelle et matière civile.* Although I'm certain that one exists, I couldn't find an English translation on Amazon.com. In any event, the history and technical details are given in F. Haight, *Handbook of the Poisson Distribution* (John Wiley and Sons, New York 1967).

[4] If x is the number of crimes that occur in a fixed area – say, one city block – in a fixed period of time – say, one year – the probability that exactly k crimes occur on any block in any year is $\text{Prob}(x=k) = \lambda^k e^{-k} / k!$ (for k = 0, 1, 2, ...). The parameter λ (lambda) is the Poisson mean, estimated in the ordinary way. In this instance, since there are 48 crime incidents scattered over 1,210,000 square feet, $\lambda = 48/1{,}210{,}000 \approx 0.00004$ incidents per square foot.

neighborhood during the next year is given by the Poisson density function,

$$\text{Prob}(x = k) = \lambda^k e^{-k} / k! \qquad \text{where } \lambda \text{ is the crime rate}$$

To illustrate how this density function works, in 2000, the robbery rate in Los Angeles was

$$\lambda = .0041 \textit{ per capita} \text{ robberies}$$

Plugging this mean into the Poisson density function, the probability a randomly selected resident of Los Angeles will be robbed in the next year is

$$\text{Prob}(x = 0) = (0.0041)^0 e^{-0.0041} / 0! \approx 0.99591$$

In the next year, 99.59 percent of the resident population will not experience a robbery in the next year. The proportion who will experience k=1 robbery is,

$$\text{Prob}(x = 1) = (0.0041)^1 e^{-0.0041} / 1! \approx 0.00408$$

which, not surprisingly, is the *per capita* robbery rate. A very small (and unfortunate) proportion of these cases will experience a second robbery. For k=2 robberies,

$$\text{Prob}(x = 2) = (0.0041)^2 e^{-0.0041} / 2! \approx 0.00000584$$

and so forth. Using the same Poisson density function formula, one can calculate the proportion of individuals who experience k = 3, 4, ... robberies. The proportions approach zero rapidly.

These probabilities apply to a randomly selected individual who spends one year wandering the streets of Los Angeles. The way think about crime rates, these probabilities are inherently temporal or longitudinal. The same Poisson density function can be used to calculate the probabilities of inherently spatial phenomena, however. To illustrate, the simulated Poisson processes in Figure 3.1 have distributed or scattered 48 crime incidents across virtually identical 1,210,000 square-foot neighborhoods. Although both Poisson distributions were generated with the same crime rate (λ=48 crimes/area/year), in terms of their visual appearance, the two distributions are as different as night and day.

Figure 3.1 Here

The left-hand distribution in Figure 3.1 is *completely random*.[5] Crime risk is distributed

[5] P.J. Diggle (*Statistical Analysis of Spatial Point Patterns, 2nd Ed.*. Arnold, 2002) uses "complete spatial randomness" as a synonym for "Poisson." The Cartesian (X_i, Y_i) co-ordinates

evenly across the blocks of this neighborhood. The right-hand distribution has the same crime rate but risk emanates from a point-source, hence the name *point-source random*.[6] As one moves away from the point-source, risk diminishes exponentially. Spatial distributions of this type rarely arise by chance alone but, in most instances, are generated by point-sources such as SOBs.

3.2 AMBIENT CRIME RISK AS A FUNCTION OF DISTANCE FROM THE SITE

Risk-distance relationships (or loosely speaking, functions) long been used to document the ambient crime risks of SOBs.[7] The model used here is an application of a statistical model that Dr. Mark Stiger and I developed some years ago for a similar problem on an isolated site.[8] The present model is adapted to multi-site analyses by incorporating appropriate error terms for the sites. The resulting family of models are known, variously, as Poisson hierarchical,[9] multi-level,[10] or random co-efficient models.[11]

At its simplest stage, the model equates the Poisson *mean* of a parcel with the *area* of the parcel and, hypothetically, with the *distance* of the parcel from the SOB. To implement this simplest model, select any of the 19 SOBs and construct 22 concentric circles (see Figure 1a) with radii of 50, 100, 150, ..., 1,100 feet from the address. The number of crime incidents in the i^{th} concentric parcel – and hence, the Poisson *mean* – is a function of the *area* of the parcel and, hypothetically, the *distance* of the parcel from the SOB site. That is,

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of the i^{th} *completely random* crime were drawn from a uniform distribution of the segment (-6,6).

[6] The polar (θ_i, δ_i) co-ordinates of the i^{th} *point-source random* crime were drawn from a uniform distribution of the segment ($0,2\pi$ for θ_i) and an exponential distribution of the segment (0,6 for δ_i). Polar co-ordinates (θ_i,δ_i) translate into the Cartesian plane as $X_i = \delta_i \cos(\theta_i)$ and $Y_i = \delta_i \sin(\theta_i)$.

[7] McPherson, M. and G. Silloway. *An Analysis of the Relationship between Adult Entertainment Establishments, Crime, and Housing Values*. Minnesota Crime Prevention Center, Inc. October, 1980.

[8] *E.g.*, in "Confirmatory spatial analysis by regressions of a Poisson variable," (*Journal of Quantitative Anthropology*, 1989, 2:13-38) Mark Stiger and I model the spatial distribution of bones at an archaeological site.

[9] Bryk, A.S. and S.W. Raudenbush. Hierarchical Linear Models: Applications and Data Analysis Methods. Sage, 2002.

[10] Goldstein, H. *Multilevel Statistical Models, 2nd Ed*. Halsted Press, 1995.

[11] Longford, N.T. *Random Coefficient Models*. Oxford University Press, 1993.

$$\lambda_i \quad = \quad \text{function}(\text{Area}_i, \text{Distance}_i) \qquad i = 1,\ldots, 22 \text{ concentric parcels}$$

A log-linear ("link") function is conventionally specified in order to take advantage of maximum likelihood theory.[12] Thus,

$$\text{Log}(\lambda_i \mid \text{Area}_i) \quad = \quad \beta_0 + \beta_1 \text{Distance}_i + \tau_i \qquad \text{where } \tau_i \sim N(\mu, \phi)$$

The stochastic term τ_i accounts for the effects of the many small measurement errors that accrue from various sources. Finally, since there are 19 distinct SOB sites, it will be useful to add a second subscript to the simple model. Thus,

$$\text{Log}(\lambda_{ij} \mid \text{Area}_i) \quad = \quad \beta_0 + \beta_1 \text{Distance}_i + \tau_{ij} \qquad j = 1, \ldots, 19 \text{ SOB sites}$$

Adding a second subscript allows for ($i \times j = 22 \times 19 =$) 418 distinct means.

The next step in the model-building process involves incorporating explanatory variables that correspond to systematic sources of variance in the λ_{ij}. Hypothetically, the Poisson mean varies by SOB subclass; bookstore-arcades and bookstores pose qualitatively different ambient risks and, thus, have distinct means. Likewise, as a matter of fact, each of the five crime categories has a distinct mean. Incorporating these two variables into the model,

$$\text{Log}(\lambda_{ij} \mid \text{Area}_{ij}) \quad = \quad \beta_0 + \beta_1 \text{Distance}_{ij} + \beta_2 \text{Subclass}_{ij} + \beta_3 \text{Crime}_{ij} + \tau_{ij}$$

Coding both variables as dichotomous (0,1) indicators allows parameters β_2 and β_3 to be interpreted as intercepts. More important for our purposes, defining both variables as dichotomous indicators allows for straightforward estimation of subclass interactions with distance and crime categories.

$$\begin{aligned}\text{Log}(\lambda_{ij} \mid \text{Area}_{ij}) \quad = \quad & \beta_0 + \beta_1 \text{Distance}_{ij} + \beta_2 \text{Subclass}_{ij} + \beta_3 \text{Crime}_{ij} \\ & + \gamma_1 \text{Subclass}_{ij} \bullet \text{Distance}_{ij} + \gamma_2 \text{Crime}_{ij} \bullet \text{Distance}_{ij} + \tau_{ij}\end{aligned}$$

Finally, to account for residual site-specific variance, independent of all other considerations, each of the 19 SOBs is allowed to have its own stochastic term. Conceptually, this can be written as

$$\begin{aligned}\text{Log}(\lambda_{ij} \mid \text{Area}_{ij}) \quad = \quad & \zeta_j + \beta_1 \text{Distance}_{ij} + \beta_2 \text{Subclass}_{ij} + \beta_3 \text{Crime}_{ij} \\ & + \gamma_1 \text{Subclass}_{ij} \bullet \text{Distance}_{ij} + \gamma_2 \text{Crime}_{ij} \bullet \text{Distance}_{ij} + \tau_{ij}\end{aligned}$$

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[12] McCullagh, P. and J.A. Nelder. *Generalized Linear Models, 2nd Edition*. Chapman and Hall, 1989.

where $\zeta_j \sim \Gamma(\beta_0, \psi)$.

Table 3.2 Here

Parameter estimates from GLLAMM in Stata Version 9.2 are reported in Table 3.2. The columns of this table defined as follows:

- The numbers in the column labeled "β" are the actual regression parameter estimates. Since these numbers are reported in the natural logarithm metric, their substantive interpretation is difficult.

- The numbers in the column labeled "s(β)" are the associated standard errors derived from maximum likelihood. The ratio of a β to the corresponding s(β) is used to test the statistical significance of an effect.

- The numbers in the column labeled "t(β)" are the ratios of corresponding β andt s(β). Under the null hypothesis, absolute values of t(β) larger than 2.0 are statistically significant at the conventional 95 percent confidence level.

- The column of numbers labeled "exp(β)" are exponentiated parameter estimates. Whereas a β is difficult to interpret, exp(β) is interpreted as the multiplicative effect of the variable. After taking care of a somewhat more important matter, I will explain how to interpret these numbers.

Since all (but one) of the t-statistics reported in Table 3.2 are statistically significant, all (but one) of the null hypotheses are rejected at the conventional 95 percent confidence level. This supports two conclusions:

- Both subclasses pose large, significant ambient crime risks; both are point-sources of ambient risk.

- Nevertheless, the ambient risks of the two subclasses are qualitatively different.

To explore the qualitative differences between the two subclasses, the parameter estimates reported in Table 3.2 were used to plot the risk functions in Figures 3.2a-c.

Figures 3.2a-c Here

Figures 3.2a-c plot the ambient risks by distance for the UCR Personal, Property, and Serious crime categories. In all three figures, the horizontal axis is calibrated in distance from an SOB site in 50-foot increments. The vertical axes range from zero to 0.0003 and are interpreted as distance-specific Poisson means.

To illustrate the interpretation of these functions, Figure 3.2a reports the means for UCR Personal crimes within 50 feet of an SOB address as

$$\lambda_{\text{combined}} = 0.000138 \qquad \text{and} \qquad \lambda_{\text{stand-alone}} = .000038$$

for the two subclasses. If these rates seem "small," it is because they have been averaged over a circular area with a 50-foot radius, an area of approximately (50 x 50 x 3.142 =) 7,855 square feet. Multiplying the two rates by 7,855 yields

$$\lambda_{\text{combined}} = 1.084 \qquad \text{and} \qquad \lambda_{\text{stand-alone}} = 0.298$$

These rates apply to the 50-foot circular parcel. If these rates now seem too "large," it is because they are integrated over the period between January 1st, 2001 and March 7th, 2007, approximately 6.18 years. Dividing $\lambda_{\text{combined}}$ and $\lambda_{\text{stand-alone}}$ by 6.18,

$$\lambda_{\text{combined}} = 0.175 \qquad \text{and} \qquad \lambda_{\text{stand-alone}} = 0.048$$

Plugging these annual rates into the Poisson density function, the probability that exactly zero UCR Personal crimes will occur within 50 feet the SOB's address of a combined bookstore-arcade is,

$$\text{Prob }(k=0) \approx \quad (0.175)^0 \, e^{-(0.175)} / 0! \approx \quad 0.8394$$

For the subclass of stand-alone bookstores, in contrast

$$\text{Prob }(k=0) \approx \quad (0.048)^0 \, e^{-(0.048)} / 0! \approx \quad 0.9531$$

The complements of these probabilities are interpreted as the probabilities that at least one UCR Personal crime will occur within 50 feet the SOB's address. For combined bookstore-arcades,

$$\text{Prob }(k \geq 1) \approx \quad 1 - 0.8394 \approx \quad 0.1606$$

And for stand-alone SOBs,

$$\text{Prob }(k \geq 1) \approx \quad 1 - 0.9531 \approx \quad 0.0469$$

In fact, these numbers are very close to what we see in the data.

Figures 3.2d Here

Figure 3.2d plots the risk ratios for the three UCR categories. For UCR Personal, Property, and Serious crime, ambient risk is highest for the subclass of combined bookstore-arcades at any distance from the address. The risk ratio of most pronounced for UCR Personal crimes, however. The rapid decay of the risk ratios with distance from the site can be deceptive. To a large degree, the distance decay reflects the simple fact that, after several hundred feet, ambient risk diminishes rapidly for all SOB subclasses.

4. SUMMARY

The findings of my analyses can be summarized succinctly. Regardless of subclass, Los Angeles SOBs are ambient crime risk point-sources. As a hypothetical pedestrian walks toward the site, victimization risk rises; walking away from the site, victimization risk falls. The nature of the ambient risk varies by subclass nevertheless. Compared to stand-alone SOBs, the ambient risk functions of combined SOBs are more acute, quantitatively and qualitatively, nearer the point-source. With respect to separating the subclasses, the difference in ambient risk functions supports the City's ordinance.

The perspective of criminological theory supports separating the subclasses of SOBs. Few criminologists would find Figure 3.2d surprising or controversial. To demonstrate this point, I will review the relevant criminological theory of secondary effects.

4.1 THE CRIMINOLOGICAL THEORY OF SECONDARY EFFECTS

Adapted to secondary effects phenomena, the routine activity theory of crime[13] holds that ambient crime risk is the product of four factors:

$$\textit{Ambient Crime Risk} \;=\; \frac{\textit{Targets} \;\times\; \textit{Value}}{\textit{Police Presence}} \;\times\; \textit{Offenders}$$

SOB sites have relatively high ambient crime risks because they attract relatively many *targets* to their sites; and because, in the eyes of the rational offender, the targets have high *values*. The

[13] This theory is due to L.E. Cohen and M. Felson, Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 1979, 44:588-608. See also, M. Felson's *Crime and Everyday Life, Second Edition* (Thousand Oaks, CA: Pine Forge Press, 1998). The routine activity theory that predicts the SOB-crime relationship is one of the most widely tested and accepted theories in modern social science. In 2005 alone, according to the *Social Science Citation Index*, the 1979 Cohen-Felson article was cited 621 times. In the last 30 years, the routine activity theory of crime risk has been tested thousands of times. Each test has confirmed the theory.

product of these two risk factors attracts predatory *offenders* with predictable consequences. Finally, since these offenders are rational, they avoid sites with visible *police presence*.

The rational offenders in this theory move freely from site to site, stopping at sites with high expected values[14] and low police presence. They are "professional" criminals in the sense that they lack legitimate means of livelihood and devote substantial time to illegitimate activities. Some are vice purveyors who dabble in crime; others are criminals who use the promise of vice to lure and lull victims. In either case, they view SOB patrons as exceptionally valuable targets.

The characteristics that give adult business patrons their high values are inherent to the commercial activities that attracted them to the site. They are disproportionately male and open to vice overtures; they carry cash; but most important of all, when victimized, they are reluctant to involve the police. From the offender's perspective, they make "perfect" victims.

The connection between crime and vice has been depicted in popular literature for at least 250 years. John Gay's *Beggar's Opera* (*ca.* 1765), *e.g.*, concerns a predatory criminal MacHeath and the vice ring composed of Lucy, Jenny, and Peachum. This popular view is reinforced by the empirical literature on criminal lifestyles and thought processes. In the earliest and best-known empirical study, Clifford R. Shaw describes the daily life of "Stanley," a delinquent who lives with a prostitute and preys on her clients.[15]

Criminological thinking on this point has changed very little in the 75 years since Shaw's *The Jack-Roller*. To document the rational choices of predatory criminals, Richard Wright and Scott Decker interviewed 86 active armed robbers.[16] Asked to describe a perfect victim, all mention a victim who is involved in vice, either as a seller or buyer. Indeed, three of the armed robbers interviewed by Wright and Decker worked as prostitutes:

> From their perspective, the ideal robbery target was a married man in search of an illicit sexual adventure; he would be disinclined to make a police report for fear of exposing his own deviance (p. 69).

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[14] If a site has N targets with values $v_1, ..., v_N$, the site's *expected value* is $E(v) = 1/N\ (v_1 + ... + v_N)$. This is the "average" that an offender would expect to take from a randomly selected victim at the site.

[15] Shaw, C.R. *The Jack-Roller: A Delinquent Boy's Own Story*. University of Chicago Press, 1966 [1930]). See also, Snodgrass, J. *The Jack-Roller at Seventy*. Lexington, MA: Lexington Books, 1982.

[16] Wright, R.T. and S.H. Decker. *Armed Robbers in Action: Stickups and Street Culture*. Northeastern University Press, 1997.

The rational calculus described by these three prostitute-robbers echoes the descriptions of other professional predators. A synthesis of the extensive literature leads to the conclusion that, from the perspective of the predatory criminal, SOB patrons are high-value targets.

Given a choice of SOB sites with roughly equal expected values, rational offenders prefer the site with the lowest level of police presence. One ordinarily thinks of police presence in strictly physical terms. An increase or decrease in the number of police physically at a site reduces ambient risk. But police presence can also be virtual through remote camera surveillance or even the presence of potential witnesses.

But whether physical or virtual, the *effectiveness* of police presence can be affected for better or worse by broadly defined environmental factors. Due to the reduced effectiveness of conventional patrolling after dark, *e.g.*, crime risk rises at night, peaking around the time that taverns close. Darkness has a lesser effect on other policing strategies, of course, and this raises the general principle of *optimizing* the effectiveness of police presence. One theoretical reason why SOB subclasses might have qualitatively different ambient risks is that they have different optimal policing strategies.

4.2 THE THEORETICAL ROLE OF SUBCLASSES

Since all SOB subclasses draw valuable targets to their sites, criminological theory holds that all will have crime-related secondary effects. Nevertheless, if the defining characteristic of a subclass affects any of the risk factors – the number and/or value of the targets at the site, the number of offenders who have pursued targets to the site, or the effectiveness of police presence at the site – criminological theory allows for qualitative differences in ambient crime risk among the subclasses.

In some instances, subclass specific risks arise because the defining characteristic of the subclass implies (or creates) idiosyncratic opportunities (or risks) for particular types of crime. Compared to the complementary subclass, *e.g.*, SOBs that serve alcohol present idiosyncratic opportunities for non-instrumental crimes, especially simple assault, disorderly conduct, *etc.* Likewise, SOBs that provide on-premise entertainment present idiosyncratic opportunities for vice crime, customer-employee assault, *etc.* Criminologists call this etiological crime category "opportunistic." There are many obvious examples and SOB regulations often treat subclasses differently because their ambient opportunity structures are different.

But in addition to subclass-specific opportunity structures, the defining characteristic of an SOB subclass may compromise the effectiveness of common policing strategies. Although the opportunity structures of combined bookstore-arcades and stand-alone bookstores present different opportunity structures, differences in the policing strategies required by the two SOB subclasses represented in this suit are a more important consideration.

In the first case, the optimal policing strategy for arcades requires that a police officer inspect the interior premises. Since this places the officer at risk of injury, policing arcades requires specially trained and equipped officers, prior intelligence, specialized backup manpower, and other resources. Since potential offenders can wait inside the premises without arousing suspicion, routine drive-by patrols to "show the flag" are ineffective.

In the second case, routine drive-by patrols are central to the optimal policing strategy for stand-alone bookstores. Since the ambient risk function for this subclass can cover a several-block area (see Figures 3a-c), drive-by patrols are an efficient way to provide a visible police presence to the neighborhood. Visibility is *per se* a deterrent. Routine patrols can keep watch for known offenders and suspicious activity. When problems are spotted, the routine patrol can forward the information to a specialized unit or, if necessary, handle it on the spot, requesting backup resources only as needed.

To some extent, differences between the optimal policing strategies for the two SOB subclasses represented in this suit amount to differences in cost. The cost of policing arcades is more expensive than the cost of policing bookstores. Even if the cost-differential were ignored, however, the optimal strategy for policing bookstore-arcades would be ineffective for policing bookstores. Indeed, neighborhood patrols by plainclothes officers in unmarked cars would be inefficient. Whereas visibility is a key component of the optimal policing strategy for bookstores, for arcades, the optimal strategy requires invisible police presence.

"Problem-oriented policing," the prevailing philosophy of policing in Los Angeles (and for that matter, in the U.S. and Europe), points to legitimate rationale for the spatial separation of SOB subclasses."[17] In simple terms, problem-oriented policing consists of analyzing a public safety problem *qua* problem; of developing an intervention that reflects the problem's unique properties and that utilizes the local environment; and of measuring the effectiveness of the intervention.[18] The analyses reported in Section 3 above demonstrate that, while both SOB subclasses have crime-related secondary effects, qualitative differences in their effects dictate very different optimal policing strategies. In light of these differences, implementing a single procrustian policing strategy for all SOB subclasses would be wasteful and inoptimal.

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[17] William J. Bratton, the current LAPD Chief, is an early, well-known proponent of problem-oriented policing. See, *e.g.*, Bratton, W.J. The New York City Police Department's civil enforcement of quality-of-life crimes. *Journal of Law and Policy*. 1994, 3:447-464; or Kelling, G.L. and W.J. Bratton. Declining crime rates: Insiders' views of the New York City story. *Journal of Criminal Law and Criminology*, 1998, 88:1217-1232. A recent speech by Chief Bratton (A Practitoner's Perspective, From the Streets. National Institute of Justice Annual Conference, July 17th, 2006) is posted on the LAPD website. For a background discussion, see Goldstein, H. *Problem-Oriented Policing*. Wiley, 1990.

[18] See, *e.g.*, National Research Council. *Fairness and Effectiveness in Policing: The Evidence*. National Academies Press, 2004.

Technical Appendices

A. Converting latitude and longitude to Cartesian Co-ordinates

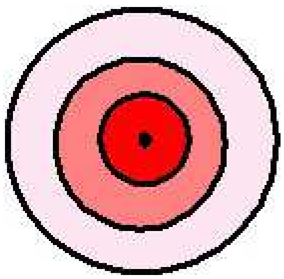
The COMPSTAT data file identified the locations of crime incidents by address and by longitude and latitude (CRIMELOCX and CRIMELOCY). The North American Datum 1927 projection was used for the co-ordinates was North American Datum 1927. To translate the latitudes and longitudes to Cartesian co-ordinates, the plotted data were read into ArcMap 9.0 and were reprojected in State Plane California 1983 (feet) area V. The results were exported to an MS Access database file.

B. Converting COMPSTAT Crime Categories to UCR Categories

UCR Part I				UCR Part II				All	
Personal		Property		Personal		Property		Other	
110	32	310	2212	250	7	442	909	234	89
210	2207	320	151	251	19	444	4	237	33
220	308	330	3248	624	4292	471	7	762	11
230	2008	331	323	626	409	474	2	805	9
231	33	341	1959	627	16	475	2	806	17
235	16	343	34	753	19	649	346	810	39
236	687	345	4	755	57	651	176	812	87
350	206	347	1	756	9	652	170	813	49
351	44	410	76	761	137	653	22	850	74
352	31	420	1147	763	23	654	20	900	251
354	432	421	8	886	83	660	15	901	85
434	2	430	3	888	302	661	4	902	3
437	7	431	1	910	44	662	27	903	10
439	4	433	4	920	14	664	14	943	5
450	5	440	2821	922	24	666	2	946	1445
451	1	441	36	928	175	668	32	954	6
622	6	480	19	930	1341	670	7	975	1
623	126	485	1	956	504	740	819	976	276
647	39	487	2	970	31	745	2294	978	518
860	182	510	3237	972	10	924	3	979	210
940	20	520	86			948	6	980	560
		521	264			949	3	986	31
		648	21					997	2889
		932	21					998	9480
		933	13					999	13009
		942	3						

950	9
951	38

Figure 1a - Concentric Parcels Centered on a Point-Source



$d = 1, 2, 3, \ldots$ parcels

Radius of the d^{th} parcel = $r\,d$ feet

Area of the d^{th} parcel = $\pi (r\,d)^2 - \pi [\, r\,(d-1)\,]^2$ square feet

Figure 1b - Mean Ambient Risk for Nineteen Los Angeles SOBs

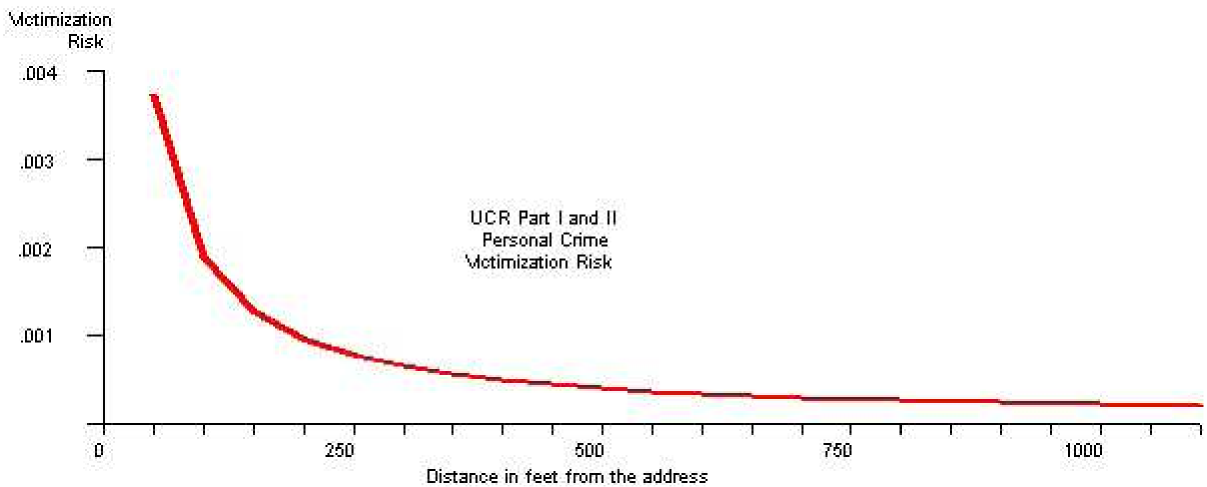


Figure 1c - Mean Risk Ratios for Nineteen Los Angeles SOBs

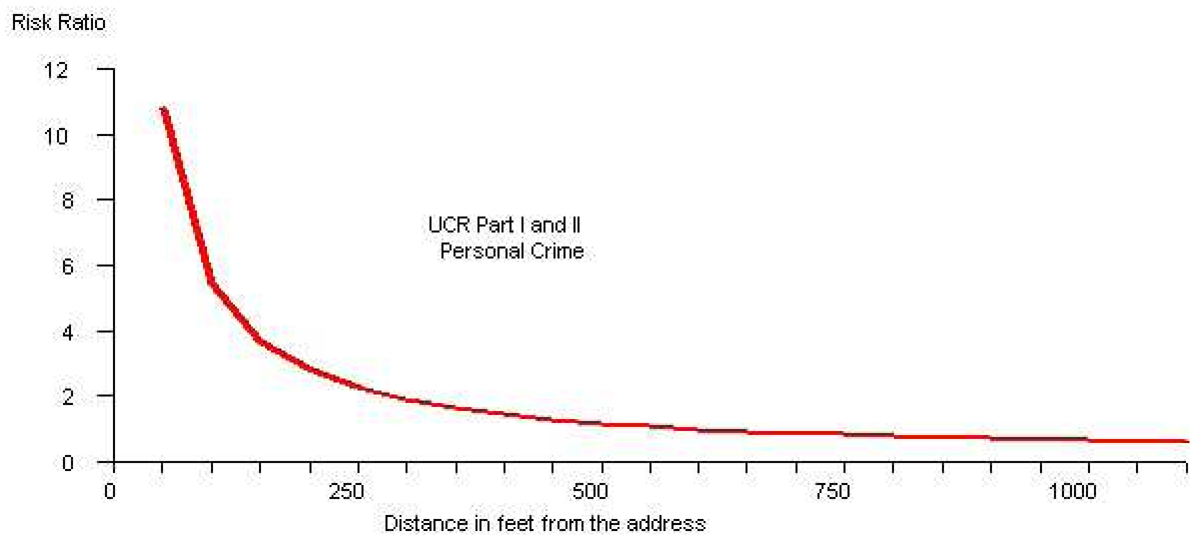


Table 2.1 - SOBs in the City of Los Angeles

Business Name	***Business Address***
Talk of the Valley	**15452 Devonshire**
Le Sex Shoppe	**21625 Sherman Way**
Sherman Way Adult Books	**11841 Sherman Way**
Drake's	**7566 Melrose Ave**
Circus of Books	**4001 W. Sunset Blvd**
Bruce & Jeffrey's Bird Cage	**12300 ½ West Pico Blvd**
Adult Video Warehouse	**9718 Glenoaks Blvd**
Le Sex Shoppe	**4539 Van Nuys Blvd**
Brand X Videos	**6161 Van Nuys Blvd**
Adult World Video	**6406 Van Nuys Blvd**
J&B Book and Video	**10930 Vanowen Street**
X-Spot 2 (*aka* Alameda Books)	**1901 S. Alameda Street, #101**
Stan's Bookstore	**1117 N. Western**
X-Spot 1 (*aka* Le Sex Shoppe)	**5507 Hollywood Blvd.**
X-Spot 3 (*aka* Highland Books)	**6775 Santa Monica Blvd, #6**
Le Sex Shoppe	**3147 N San Fernando Road**
Le Sex Shoppe	**4877 Lankershim Blvd**
Le Sex Shoppe	**12323 Ventura Blvd**
Jasons II	**6408 Tujunga Ave**
Le Sex Shoppe	**6315 ½ Hollywood Blvd**

Bookstores **Bookstore-Arcades** **Excluded from sample**

Table 2.2 - Total Crimes, Jan 1, 2001 - March 6, 2007

	UCR Personal		UCR Property		
	Part I	**Part II**	**Part I**	**Part II**	**Other**
15452 Devonshire	207	157	631	322	123
21625 Sherman	195	188	468	199	227
12300 W. Pico	51	47	149	38	105
7566 Melrose	177	157	588	266	127
4001 W. Sunset	138	182	438	130	108
11841 Sherman Way	68	35	274	44	84
9718 Glenoaks	10	12	109	21	29
Subclass Mean	**120.9**	**111.1**	**379.6**	**145.7**	**114.7**
1901 S Alameda	91	46	362	28	119
6775 Santa Monica	516	541	1192	238	229
1117 N. Western	745	603	878	525	300
5507 Hollywood	563	560	1045	460	273
3147 N. San Fernando	125	121	710	108	109
12323 Ventura	75	74	363	166	70
4539 Van Nuys	148	220	620	223	211
4877 Lankershim	207	179	808	161	180
6161 Van Nuys	225	590	498	236	495
6406 Van Nuys	317	537	730	275	271
10930 Vanowen	111	147	383	62	99
6408 Tujunga	67	62	234	45	109
Subclass Mean	**265.8**	**306.7**	**651.9**	**210.6**	**205.4**

Figure 3.1a - Simulated Spatial Distributions of 48 Crimes

Completely Random ***Point-Source Random***

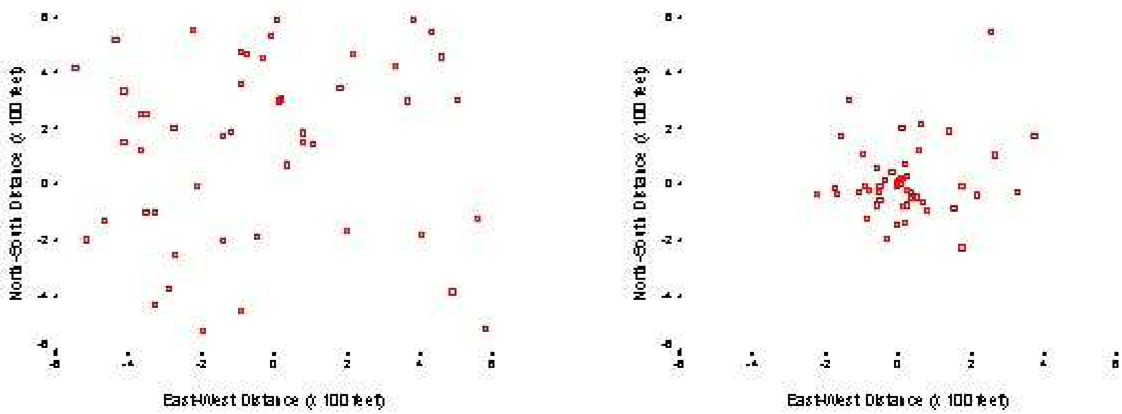


Table 3.2 - Parameter Estimates for the Poisson Regression Model

	β/γ	$s(\beta/\gamma)$	$t(\beta/\gamma)$	$\exp(\beta/\gamma)$
Constant	-9.6311	0.24454	-39.38	.00007
Distance	-0.0011	0.00005	-20.64	0.999
Combined SOB	0.8117	0.29833	2.72	2.252
UCR Personal	-0.4886	0.05264	-9.28	0.613
UCR Property	0.2824	0.04842	5.83	1.326
UCR Serious	0.7033	0.03366	20.89	2.020
Combined • Distance	-0.0003	0.00006	-5.51	0.999
Combined • Personal	0.4932	0.05853	8.43	1.638
Combined • Property	0.1320	0.05436	2.43	1.141
Combined • Serious	-0.1299	0.03722	-3.49	0.878
ζ	0.3422	0.10854		

Figure 3.2a - Victimization Risk by Distance from Site, UCR Personal Crime

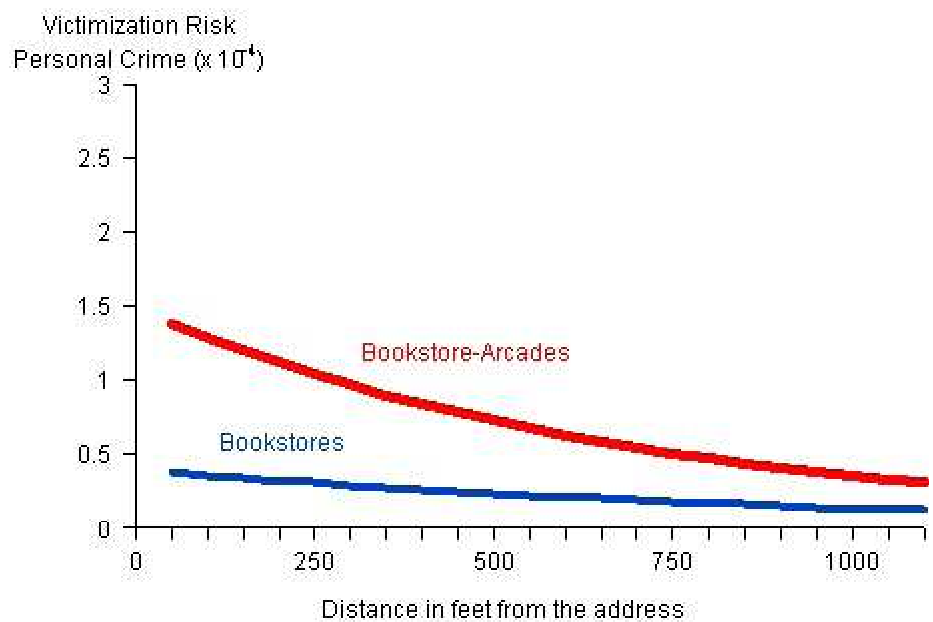


Figure 3.2b - Victimization Risk by Distance from Site, UCR Property Crime

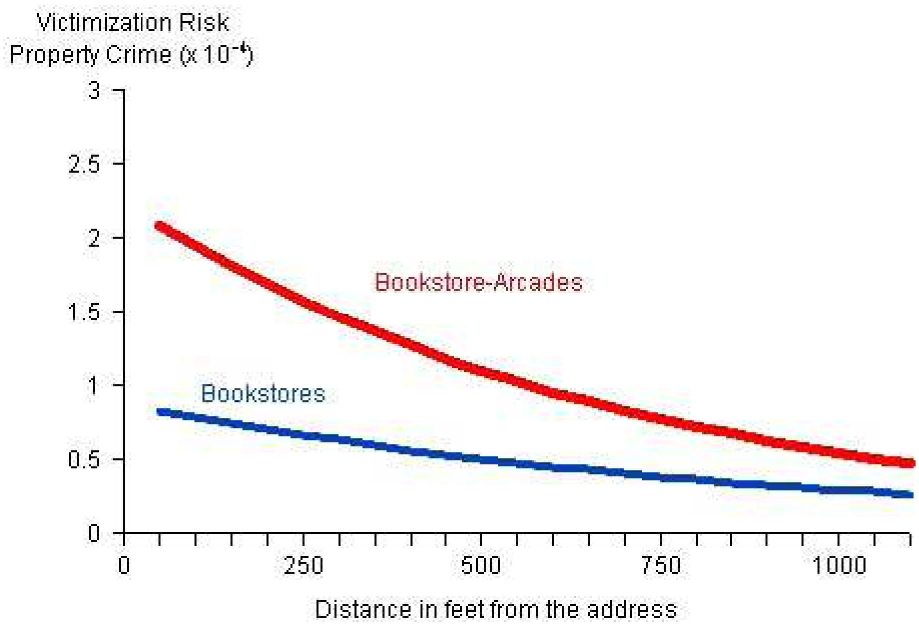


Figure 3.2c - Victimization Risk by Distance from Site, UCR Serious Crime

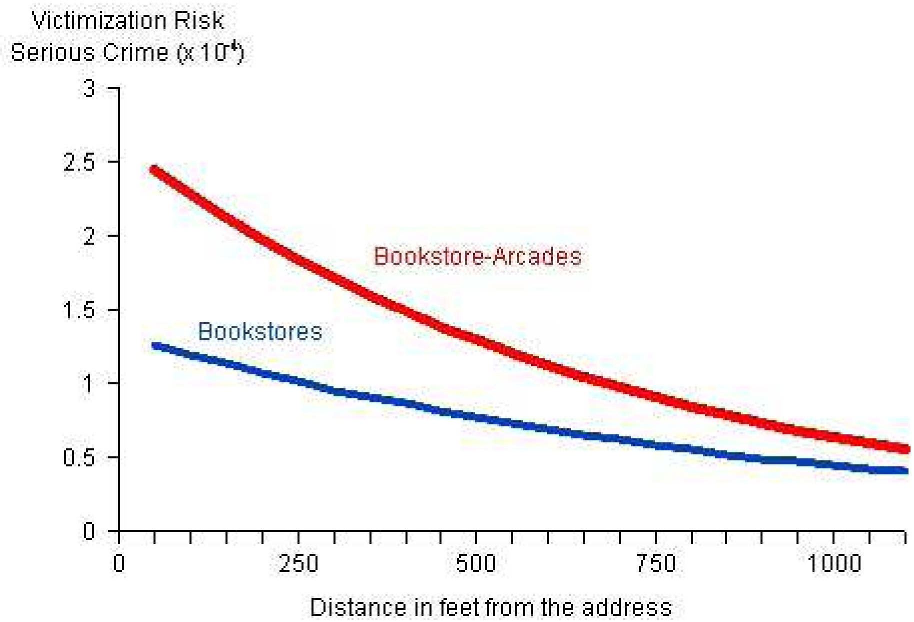


Figure 3.2d - Risk Ratios for Three UCR Crime Categories