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An Empirical Test of Opportunity Theories of Victimization: Multi-Level and Domain-Specific Models

An Executive Survey

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Introduction

Over the past fifteen years there has been a substantial growth in the use of criminal opportunity theories to explain spatial patterns of crime (Jacobs, 1961; Newman, 1972; Brantingham and Brantingham, 1981), macro crime trends (Cohen and Felson, 1979; Cohen, Felson and Land, 1980; Cantor and Land, 1985) and individual victimization risk (Hindelang, et. al. 1978: Sparks, 1981; Garafalo, 1987; Hough, 1987). The increasing popularity of opportunity theory is due to its theoretical and practical potential. Earlier theories of crime focused almost exclusively on explaining criminal motivation. Opportunity theory changed the focus of the field to explaining the occurrence of victimization This fundamental reorientation offers a fresh and stimulating perspective. The implications of opportunity theory for policy are also promising. It suggests that crime can be reduced by changing the victim or the target rather than devising deterrent or rehabilitative strategies to change the behavior of the offender. On its face, the former seems more amenable to change than the latter.

Despite the intuitive appeal of this idea and the existence of a general opportunity model, refinement of that model has not proceeded quickly. A number of the basic tenets underlying opportunity theory have never been tested. Many of the concepts used in the general framework have remained abstract and ill-defined to the point that they can not be used unambiguously to predict the occurrence of victimization. There is no standard set of concepts that researchers use when discussing or testing opportunity theory. More importantly, little research has been done on the limits of the theory for the wide range of events included within "predatory crime". Rather, the same general framework has been applied to all types of crime.

Opportunity theory will reach its potential only if there is a continuous cycle of conceptualization and empirical testing that will yield the required conceptual specificity and the knowledge of the theory's limits. This project begins one such cycle. We seek to refine the general opportunity model by introducing two conceptual/methodological innovations—multilevel and domain-specific models. These innovations should permit the testing of tenets heretofore assumed. They should also afford greater specificity in the definition and measurement of concepts and suggest where opportunity theory is most appropriate for predicting and understanding victimization.

Multi-level models predict victimization of persons or households using both attributes of these units and characteristics of larger aggregates, e.g. neighborhoods and communities, to which these units belong. Multi-level models permit more direct tests than previously possible of the importance of the concept "proximity" relative to other concepts in the opportunity model, e.g.exposure. Within opportunity

theory, the concept of proximity is the intuitive notion that if one routinely conducts activities near motivated offenders, the risk of crime will increase. ¹ Empirical research, however, has not gone much beyond this intuitive idea. The multi-level models presented below will estimate the effects of opportunity variables within ecological contexts, i.e. neighborhoods, that constitute differing degrees of proximity to potential offenders.

Domain-specific models of victimization predict categories of crime defined by activity at the time of the incident, rather than more familiar crime classes defined exclusively by the nature of the criminal act, e.g. assault. By restricting our attention to crimes occurring in one particular domain of activity, e.g. at home, at school, at work or at leisure, we hope to provide more rigorous empirical test of opportunity theory than that possible with more general models. Domain-specific models of victimization should improve the measurement of opportunity concepts over that possible in more general models. While it is difficult to define and measure opportunity concepts in a way that will be pertinent to all activity domains, it should be easier to measure these concepts in one particular activity such as work. This improvement in measurement should facilitate the identification of relationships between opportunity concepts and victimization, if these relationships exist. Moreover, by defining crimes according to activity at the time of the incident, we should be better able to establish the causal link between activity and risk than in more general models. In predicting assault, for example, we may find a relationship between labor force participation and victimization. Unless we know that the assaults in question occurred at work, the observed relationship may be due to something other than If we restrict our study to victimizations occurring at work. work, we can feel more confident that the relationship between attributes of work and victimization are indeed causal rather than spurious.

The first of the following sections reviews the basic

In using the concept proximity, we do not necessarily assume that the world is divided into those who are predisposed to be criminal and those who are not. While proximity acknowledges this difference, it also refers to the social organization of places that are more conducive to the occurrence of crime. In this case, the crime event is the product of that social organization rather than the pre-existing motivation to offend. Take, for example, the situation of an estranged husband who breaks into his wife's apartment to reclaim his bowling trophy. He did not come predisposed to burglary or larceny. In his mind the apartment and the trophy are still his. In this social context the rights of property are ambiguous and this generates the crime.

opportunity framework. The second section describes the multilevel models and presents empirical tests of same. Particular attention is given to methods for defining ecological contexts using the National Crime Survey (NCS) and for using these contexts as indicators of "proximity". The third section describes and tests domain-specific models for victimization at home, work and leisure. These models are used to evaluate the usefulness of domain-specific models as a strategy for building opportunity theory. The fourth and final section draws the implications of these multi-level and domain-specific models for opportunity theory, future research and policy.

The Opportunity Model

Opportunity theory is based on the premise that criminal events are the product of the convergence in space and in time of motivated offenders and suitable crime targets in the absence of capable guardians (Cohen and Felson,1979). Both targets and offenders are necessary elements of the event. If either targets or offenders are absent, no crime will take place. The elaboration of opportunity theory requires the identification of factors that affect the number and availability of crime targets. In the most formal exposition of an opportunity model, Cohen, Kluegel and Land (1981) identify four factors that affect victimization risk:

- 1) Target Exposure--The visibility and physical accessibility of the target.
 - 2) Guardianship--The ability of persons or objects to prevent crime from occurring.
 - 3) Target Attractiveness--The material or symbolic value of persons or property.
 - 4) Proximity--The physical distance between areas where potential targets of crime are and where large populations of potential offenders are found.

All structural factors, e.g. socio-demographic characteristics of victims, or mediating factors, e.g. routine activities, influence the risk of victimization through one of these four concepts. For example, social class will determine the amount of discretionary income available for pursuing leisure activity. The amount of time in leisure activity will affect the amount of time that you are out of the home. Time out of the home will determine the degree to which you and your possessions are exposed. The extent of exposure will determine your risk of victimization.

Empirical tests of opportunity theory have attempted to confirm the general utility of this framework and elaborate it. In view of this work a number of modifications seem in order. First, the causal ordering of concepts should be changed. original framework exposure, guardianship, attractiveness and proximity occur simultaneously. Yet it is difficult to conceive of a situation in which living or working near offenders does not increase exposure. Similarly, attractiveness requires knowledge of a target and the probability of having this knowledge is influenced by proximity. It would seem appropriate, therefore, to place proximity prior to the other opportunity concepts in the model. Proximity should be a predictor of exposure, guardianship Second, the model should clearly recognize and attractiveness. the multi-level nature the victimization process. concepts like proximity can be ecological or contextual in nature as well as individual. Nearness to potential offenders affects all residents of a particular neighborhood equally, while their individual routine activities or security precautions may raise or lower their individual risk of victimization. Distinguishing between these individual and ecological effects can offer a better idea of which elements of risk can be addressed individually as opposed to collectively.

Third, this model should assume that all of the variables included therein interact to influence exposure, guardianship and attractiveness rather than acting independently. This is consistent with the notion of a multi-level causal process in which context will effect the importance of other opportunity variables in determining risk. Fourth, within the concept proximity, associations should be included in this model to distinguish the effects of simple propinquity from those resulting from having potential offenders in one's social networks.

When these changes are introduced into the basic opportunity framework, the resulting model looks like that presented in Figure 1. Context refers here to characteristics of ecological units that affect either proximity to offenders or other characteristics of an area that influence the location of crime. Lifestyle includes routine sustenance and leisure activities. Association refers to "more or less sustained personal relationships among individuals that evolve as a result of similar lifestyles and hence similar interests in shared by these individuals" (Hindelang, et. al., 1978).

Estimating Multi-level Models of Victimization

Very few studies have estimated multi-level models of risk similar to that presented in Figure 1 because few data bases have both the necessary information on macro environments and

individuals and the requisite sample size. Studying rare events such as victimization demands large sample sizes that are usually available only from large scale surveys designed to produce estimates for nations or states. Multi-level analyses require clustering observations within sampling units in order to obtain estimates for ecological units such as blocks or neighborhoods. Clustering observations in this way substantially reduces the efficiency of samples used to produce national or state estimates. Consequently, most data bases offer the sample size or the necessary cluster, but not both.

Segment Aggregation and Area Typologies

The NCS faces the same tradeoff between efficiency and cluster, but certain features of the survey design offer the possibility of estimating multi-level models. Specifically, the NCS clusters observations in segments of four contiguous household units and returns to these units seven times in three and one-half year period. It is possible to accumulate the information within segments over those seven visits and thereby obtain reasonably reliable estimates of victimization in these small geographical areas—segments. This information on segments can be merged with the individual and household level data in the survey. If this method is successful, then the NCS could provide all the requisites for multi-level models of victimization—sample size and reliable information of both individuals and ecological units.

On its face this approach offers some advantages for exploring multi-level models. Previous multi-level research has been limited because the ecological unit available was relatively large, e.g four contiguous enumeration districts or and electoral district, and, therefore heterogeneous. In contrast. segments are four contiguous housing units which are likely to be better indicators of the area immediately surrounding a particular unit.

The principal disadvantage is the lack of correspondence between the unit of aggregation and the theoretical process. Using segment will not adequately measure context if most of the areal differences in crime are between larger aggregates such as neighborhoods or communities. If this is the case, then larger clusters would be in order. One way to test the extent of this problem is to examine the percent of variance in crime accounted for between segments. If crime does not cluster by segment, then clearly the importance of this areal unit for understanding risk is questionable. When this was done, a significant amount of clustering was found to occur for NCS segments. This tends to support the use of segments as an ecological unit for exploring victimization risk.

Estimating the multi-level model with the NCS proceeded in three stages. First, segment level crime rates were computed.

Second, these rates were entered into a clustering program to identify area types. Third, the resulting types were used as indicators of residential location as indicated in figure 1.

Segment crime rates were computed by aggregating crime reports for all NCS rotation groups that could have completed seven interviews between 1979 and 1983. For each of these segments, we computed four different crime rates—1)serious violent crime, 2) personal theft away from home, 3) burglary and 4) household larceny. The areal typology was formed by distinguishing urban from rural segments and by the covariation among the four different crime rates using latent structure analysis. This analysis produced three area types. (table 1) The first was an area with extremely high crime rates, including serious violent crime. The second area type was marked by extremely high property crime, both burglary and home larceny. The third area, which included the majority of segments, were low crime areas.

It should be noted that the distinction between the high crime and the high property crime areas is not extremely significant. This implies that there is very little areal specialization in the type of victimization. However, that the overwhelming majority of segments are included in the low crime classification indicates that victimization is highly clustered geographically.

Describing Area Types

If opportunity theory is useful for understanding differences in the spatial distribution of crime, then differences in opportunity concepts should predict differences in area types. High crime segments, for example, should be characterized by high proximity and relatively low guardianship. Property crime segments should be lower on proximity and low on guardianship, but high on exposure and attractiveness. The low crime segments should be low on all four dimensions.

Measures of exposure, guardianship, attractiveness and proximity were computed using data from the Victim Risk Supplement (VRS). The Supplement included much more specific information on opportunity concepts than that available in the standard NCS. This information was aggregated to the segment level and used in a discriminant function analysis to predict location in the areal typology. The specific measures of opportunity concepts used in the analysis are presented in Table 2.

The results of the analysis are presented in Table 3. The table includes only those variables that had a statistically significant effect on predicting area type or those that were not statistically significant, but are theoretically interesting.

Two canonical variants were extracted. Both were statistically significant, but they explained a relatively low proportion of the variance (12%). The results generally support the importance of proximity in predicting segment crime patterns. The first factor is the most powerful. It distinguishes the high from the low crime segments. Within this factor, indicators of proximity are the most powerful discriminators. The strongest are the fear measures (proximity), the number of offenders perceived as coming from inside the neighborhood(proximity), the number of owner occupied units (proximity) and the percent of persons (proximity). There are other selected measures of exposure, attractiveness and guardianship that are moderately helpful in distinguishing high from low crime areas. The presence of neighborhood watch groups does not seem to make a big difference in differentiating high from low crime areas. Neither does the willingness of neighbors to watch each others home. This would suggest that in terms of crime prevention, these guardianship measures do not have a large effect on the target selection. This is consistent with the notion that high crime areas are primarily the result of proximity rather than other opportunity concepts.

The second canonical variant distinguishes between high crime areas and property crime areas after the first variate is held constant. The results indicate that the distinction between these types of areas cannot be cleanly made, since the squared canonical correlation for this variate is only .03. Nonetheless, there are some interesting differences between the areas. Property crime areas have higher income (attractiveness) than high crime areas and they are more likely to have single family units (guardianship). This suggests that given proximity, areas with attractive targets and low guardianship will have high property crime. The strongest discriminator, however, is in the opposite direction from that predicted by opportunity theory. The prevalence of self-protective devices is much higher in areas of high property crime than it is in high crime areas. similar, but less powerful effect was found for neighborhood watch and for watching neighbors houses. These protective measures are taken more frequently in property crime areas than in high crime areas. These findings are consistent with the image of the "defended community"--proximate to dangerous areas and self-consciously defending itself against predation from the In higher crime areas predation is often from the inside and they lack the social organization to mobilize for defense.

In sum, the results of the discriminant function analysis indicate that proximity is the most important of the opportunity variables for predicting inter-area crime patterns. The differences across the three types of crime areas could be predicted most cleanly by the measures of proximity included in the analysis--fear, number of offenders living in the area and

prevalence of younger persons. The distinction between high crime areas and high property crime areas is not as cleanly made. This would suggest that while there are differences between high crime and high property crime areas, the major distinction is between high crime and low crime areas and that distinction is a function of the proximity of potential offenders. When proximity is held constant, however, several attractiveness and exposure variables predicted high property crime areas in ways consistent with opportunity theory. These findings then seem to support the use of opportunity concepts to explain areal variation in crime. They also seem to support the preeminence of proximity within the opportunity framework.

These results also raise questions about assuming that the "victim" and "offender" populations are distinct and mutually exclusive. The fact that victims of violent crime seem to be as highly clustered geographically as offenders and are located in similar neighborhoods suggest that the two populations may overlap for many types of crime. Theories or policies that treat these populations as mutually exclusive may be misleading.

Estimating the Interaction Between Individual and Contextual Factors

Specifying the effects of individual and contextual variables is important for developing theories of crime and policies for crime control. Many of the empirical tests of opportunity theory take the victim as the unit of analysis and ignore contextual effects. This can result in erroneously attributing causality to the characteristics of individuals, when it is actually the nature of the residential area that puts persons at risk. Moreover, individual and contextual factors can interact in ways that increase risk for particular types of people in specific types of areas. These interactions can only be identified with multi-level models. To the extent contextual variables mediate or interact with individual characteristics, the knowledge derived from single level models will mislead policy. So, for example, individual level analyses may indicate that older persons have lower risk of victimization than younger persons, while multi-level models may indicate that older persons in areas proximate to offenders have a higher risk of victimization than younger persons generally or younger persons in high risk areas. Targeting resources and directing policy on the basis of individual models, then, would result in under-protecting a high risk group.

The joint effects of contextual and individual variables on risk of victimization were estimated using NCS data. The analysis was restricted to property crimes occurring around home, i.e burglary and home larceny. We focused on crimes at home because the NCS does include information on risk factors for

locations immediately outside of the respondents sub-block. Consequently, the data are best for exploring crimes at or near home. Property crimes were chosen because there are simply not enough violent crime in the NCS to conduct meaningful multi-level analysis of crimes at home.

The segment level variable in the model was a modified version of the area typology described in the previous section. Four area types were used.² The address segments were divided into high crime, low crime and high property crime segments. The area segments were treated as a fourth type. This fourth type was included to permit comparisons between rural and urban areas. Recall that the earlier typological work only included address segments.

Individual level data was taken from all NCS rotation groups that could have completed all seven interviews between 1979 and For each respondent in these rotation groups, the individual data used was taken from their second interview or their second time in sample. The individual-level characteristics used in the analysis were selected on the basis of their theoretical and empirical significance as indicated by previous work(Cohen, et.al. 1981; Hindelang, et.al. 1978). included 1) age of the household head, 2) race, 3) marital status, 4) family income, 5) and number of units in the dwelling. some respects, the use of socio-demographic characteristics of respondents to represent individual level opportunity concepts is not ideal. More direct measures, such as those available in the VRS, would have been preferable. Unfortunately, the VRS is not large enough to sustain a complex analyses in which a great number of interactions are possible. Moreover, a great deal of the empirical literature on opportunity theory has used these proxy measures for opportunity concepts. This literature serves as the basis for our expectations about factors affecting risk.

 $^{^2}$ The use of crimes as dependent variables and the areal typology as an independent variable does build in some weak dependence between the two variables. The typology is based upon reports of crime in the segment and the dependent variable is a report of crime occurring in that segment. The fact that the typologies are formed with four different crime rates and on the basis of seven different interviews for all persons in the segment removed a large part of this dependence. The dependent variable is the report of crime by a single respondent for a single time in sample. In order to check for the degree of dependence in the variables, we re-classified segments excluding the report of crime that was used as the dependent variable. Only 1.7 % of the segments in the high crime area were reclassified and 2% of the segments in the property crime area This relatively weak dependence did not pose a major threat to the validity of this analysis.

It is useful for purposes of theory building to see how the introduction of contextual variables changes the results and thereby, our expectations. To the extent that this previous empirical work has guided the targeting of resources, then these changes will also be of interest for policy.

The dependent variable was a prevalence measure which categorized households in two categories--no victimizations reported and at least one victimization reported.

Multi-level models were estimated using log-linear analysis (Goodman, 1974) This technique allows for reliable and relatively inexpensive estimation of both partial and higher order effects when the dependent variable is both dichotomous and highly skewed. In addition, log-linear analysis permits ready inspection of relevant marginal cells critical for estimating interactions. This is especially important given the relatively small sample sizes available for this analysis.

The analyses, performed separately for burglary and home larceny, were done in two steps. In the first step, the model was estimated using only individual socio-demographic variables. The model was re-estimated in the second step including the areal typology. This two step procedure made apparent how the introduction of the contextual variable changed the effects of individual variables.

For burglary (Table 4), age (proximity), marital status(guardianship), and race (proximity) are related to victimization in ways consistent with opportunity theory when area type is not in the model. Younger persons are at greater risk of burglary than older persons; married persons are at less risk than non-married persons; and non-whites have higher risk than whites. Income (attractiveness and proximity) is related to victimization, as the theory would predict, but the effect is not very strong. Lower income persons and higher income persons are at greater risk than middle income persons. Presumably, the former effect is due to proximity and the latter to attractiveness. The effect of the number of units in the structure (guardianship) on burglary is the opposite of that predicted by opportunity theory—single family structures are at less risk than multi-unit dwellings.

When the areal typology is entered into the models (Table 5), some of these partial effects of individual characteristics disappear and others are mediated by the type of residential area (proximity). The effect of race disappears when area type is entered into the model. In all of the models estimated there is a significant three-variable interaction between age, area type, and victimization. Households with heads 65 or older living in violent crime areas are at greater risk than we would expect given their age and location. Similarly, persons 50 to 64 living

in high property crime areas are at greater risk of burglary than expected. The effect of age on risk goes to zero in high crime areas and increases in low crime areas. The effect of marital status (guardianship) on risk is also affected by type of residential area in which respondents live. When area type is introduced into the model, the effect of marital status is reduced in high crime and high property crime areas. It remains the same in urban low-crime areas and substantially increases in rural areas. The change in the effect of income (attractiveness) on risk is similar to that for age and marital status. Living in high crime areas tends to decrease the relationship between income and risk, while living in low crime areas tends to increase the effect of income on risk. Increases in income result in greater risk in low crime areas than they do in high crime areas. There is no interaction between the number of units in a structure, area type and burglary.

The results of the home larceny model are quite different (Tables 6). While individual characteristics are related to risk of home larceny in the directions predicted by opportunity theory, there are no significant interactions between these characteristics and area type (Table 7). Younger persons (association) are at greater risk than older persons; married persons are more often victimized (presumably because of they have more goods to steal) than unmarried persons; middle income persons (attractiveness) are more often victims of home larceny than lower income persons; the larger the housing unit (the greater the confusion of public and private space and the lower the guardianship) the higher the larceny rate. Area type does not interact with individual characteristics, although the effect of race goes to zero when area type is introduced.

Several conclusions can be drawn from the foregoing analyses. First, there is very little areal specialization in victimization. There are high crime and low crime areas, but not areas that are high on one type of crime and not others. Second, criminal victimization is highly clustered geographically. majority of areas are crime free for long periods of time, i.e. 3.5 years. Third, different opportunity models must be used to predict risk of burglary than are used to predict home larceny. Specifically, the type of area in which one lives interacts with other opportunity concepts such as attractiveness, exposure and guardianship to determine the risk of burglary. The nature of the residential area affects the risk of home larceny, but area does not interact with other opportunity variables to determine that risk. So, for example, target attractiveness will increase risk of victimization regardless of the type of area one lives This is not the case for burglary. The effect of income, for example, varies significantly by whether a person lives in a dangerous or safe neighborhood. This interaction implies that opportunity processes differ not only by type of crime, but also by type of area. Finally, area type mediates the effect of race

on risk of burglary and home larceny. Non-whites are at greater risk than whites because non-whites live in more dangerous areas than whites. When area type is held constant, the risk of victimization across racial groups does not differ.

Constructing Domain-Specific Models of Victimization

Domain-specific models refers to the practice of subdividing both crime and indicators of opportunity concepts in order to avoid the pitfalls of overly general conceptual and empirical A domain is an amalgam of location and activity. models. work domain, for example, includes both events that happen at the work site and while the victim is performing the work role. restricting attention to events occurring in a particular domain, we can develope more specific conceptual models that can be operationalize more easily. First, the definition of major independent variables such as exposure or guardianship can be made more clearly when the model pertains to one domain rather than all places or behaviors. Second, measuring concepts is simplified and improved when concepts are more clearly defined. Third, defining crime by virtue of the activity of the victim at the time of the event simplifies drawing the causal link between activity and victimization. If a crime occurs at work, for example, we can safely exclude non-work activities as the proximate causes of the event and focus on features of the work. Finally, domain-specific models provide an incremental approach to building a more general opportunity theory of criminal victimization. Domain-specific models can be developed tested and then compared to see if a more general theory of opportunity applies equally well in all domains.

Phrases such as, "at school" or "at work" or "at home", are commonly used as a shorthand way of referring to distinct social spheres. We are comfortable using these phrases to describe where people are and what they are doing because they describe a discreet set of behaviors and social contexts. These domains are also inclusive of a great deal of human activity and a great deal of the victimization befalling persons. The distinctiveness of behavior in these domains and the inclusiveness of just a few domains suggests that estimating domain-specific models may provide the specificity needed for good measurement and the inclusiveness necessary for parsimony. For these reasons, we divided victimization and indicators of opportunity concepts into four domains--"at home", "at work", "at school" and "at leisure".

The home domain includes victimization and indicators of opportunity concepts occurring at or near the home. The work domain includes victimization that occurs at the work location or while someone is on duty regardless of the location. It also includes attributes of the work environment that can serve as indicators of opportunity concepts. The school domain refers to

events that happen on school grounds. Leisure is a catch-all category that includes victimizations that occurred away from home school or work and while the victim was "out for the evening", "shopping", "traveling locally or extra-locally", or "commuting to work".

Estimating Domain-Specific Models

In order to test the utility of domain-specific models, we divided victimization and indicators of opportunity concepts into the four domains described in the previous section. The victimization rates for these domains are presented in Table 8 and discussed in the next section. We defined an opportunity model for each domain and tested that model. The results of these tests are discussed briefly below. Finally, we compared the results of these models to more general models of risk to determine whether domain-specific models provide the expected improvements in measurement.

The Distribution of Crimes Across Domains

Over three quarters of all the victimizations reported in the VRS were included in four domains—home, work, school and leisure. Of those crimes that could be classified 38.5% occurred at home, 20.5% happened in the work domain, 14.8% took place in the school domain, and 26.1% occurred at leisure. Events that could not be accommodated within the four domains fell into two categories—crimes that occurred in the residential neighborhood, i.e. within one mile of home, and crimes in which a motor vehicle was the object of crime. Motor vehicle crime has been examined elsewhere (Lynch and Biderman, 1984).

The distribution of victimizations by domain is enlightening because it complicates preexisting wisdom about the social context of victimization risk. We have come to assume that work is a safe place while leisure activity is risky (Hindelang, Gottfredson, and Garafalo, 1978), but a good deal of victimization occurs at work (Collins, Cox, and Langin, 1987; Lynch, 1987). Moreover, denoting victimization by activity gives potential victims and policy makers a much clearer reference as to when they will be victimized. Knowing that a substantial proportion of crime occurs at work suggests that we may want to direct crime

Approximately 50% of the unclassified incidents reported in the VRS are crimes in which a motor vehicle is the object and 38% of these crimes take place in the area immediately around the home—the neighborhood—and do not involve motor vehicles as the object. Only 12% of the unclassified incidents do not fall in one of these two categories.

control resources toward the work place rather than focusing almost exclusively on residential communities.

Domain-Specific Victimization Rates

The distribution of victimization incidents presented in Table 9, cannot be interpreted as a risk rate. The distribution of victimizations by domain could be due to the fact that persons or their property are more often in one domain than another. We must account for differential rates of participation in one or another activity domain before we can speak about differential risk across activities.

Computing Denominators.

Obtaining the appropriate denominator for a domain-specific risk rate is difficult. Where behavior is discrete such that participation or eligibility is complete or non-existent, as mortality, then a simple count of persons participating or at risk is sufficient. When participation can vary in degree, the denominator of the risk rate must reflect that variation. Participation in activity domains is of the latter type. Consequently, some measure of time spent in each domain would be the most desirable denominator for a risk rate. The VRS did not include any time budget questions regarding time at home, at school or at leisure, so rates based on time spent in a particular activity cannot be computed. Some crude risk rates can be computed, however, using discrete participation measures for a rate base. For example, a victimization rate for work can be computed by dividing victimizations at work by the number of people in the work force.

The VRS includes the standard labor force items on the major activity of respondents in the week prior to the interview. These questions were used to indicate who is in the labor force and who is in school. Persons in the labor force were used as

⁴Data on hours worked in a week are available in the VRS, but it would be somewhat inappropriate to compare the refined work risk rate with the crude rates computed for other domains.

⁵ A more vexing problem in deciding upon the denominator of a risk rate is identifying both the persons <u>and</u> their property at risk. The period of risk for property may be different than the period of risk for persons who own that property. Accounting for the amount of property at risk is also problematic. The sheer volume of personal property available in some domains may be substantially different from that available in others.

⁶ Persons coded as 1, 2, and 8 on variable 2034 were considered in the work force. Those coded 5 and 99 on this variable were considered as attending school. All persons were included in the denominator of the home domain risk rate. All

the base for a risk rate at work and persons in school were used as the basis for a risk rate in the school domain. Since everyone participates in the home domain in some capacity, the total population can be used as the rate base. To a lesser extent, this is true for the leisure domain.

Numerators of the Rate.

The numerators for the rates are the number of crimes reported as occurring while the respondent was pursuing a particular activity. 7

Risk Rates by Domain

When domain-specific victimization rates are computed on the base of those engaged in the activity school is by far the most dangerous activity. The overall victimization rate for the school domain is 2.9 times that of the leisure domain, 2.0 times that of the home domain, and 1.8 times that of the work domain. In spite of the crudeness of the rate bases used here, it seems clear that the risk of victimization is greatest at school.

The high risk rate for work is particularly surprising. The risk of victimization at work is essentially equal to the risk at home and 60% higher than the rate at leisure. The fact that risk of victimization at work is approximately equal to that at home is noteworthy because the bulk of the property at risk in the work place is commercial property which is excluded from the NCS. The majority of property at home is private property which is included in the survey. The amount of property at risk at work and eligible in the NCS is substantially less than that at risk at home, but the overall victimization rate is essentially the same. This makes work a more dangerous place.

The risk of being a victim of violent as opposed to property crime varies considerably across domains. The risk of violent victimization is low in all domains—.01 or less. It is highest at school and work, followed closely by leisure, and it is lowest at home. The probability of being a victim of violent crime at home is approximately 30% that of being the victim of violent

persons except those who claimed that they never shopped or went out for the evening were included in the denominator of the leisure domain risk rate.

⁷ The particular method used to obtain these numbers is presented above on pages 9 and 10 above.

crime at school or at work.8

The risk of property crime is greatest at school, followed distantly by the home domain, work and leisure. The risk of property crime at school is 1.9 times that at home, 2.2 times that at work, and almost 7 times the risk at leisure. This is truly astounding when you consider that the amount of personal property available for stealing at school is considerably less than that at home. The relative ranking of the home, work and leisure domains is consistent with the apparent availability of property for stealing.

These differences in crude risk rates confirm some of the common wisdom about victimization and challenge other aspects of it. They confirm that school is an incivil place both in terms of violent and property crime (Garafalo, Siegel and Laub, 1987). They also confirm that home is a relatively safe place with regard to violent crime, but dangerous with respect to property crime. Surprisingly, work is a relatively dangerous place for both property and violent crime and leisure is generally a safe activity.

Domain Specific Victimization Rates for Demographic Groups

These differences in risk across domains may be due to the nature of the routine activities pursued or other aspects of the domain. They can also result from the types of people who engage in the activity. Younger people, for example, are more often victimized than older persons. Consequently, domains that involve a disproportionate amount of younger persons can have higher risk rates because of the over representation of victimization-prone persons. In order to test the importance of activity (as indicated by domain) as opposed to the characteristics of participants for explaining differential risk across domains, we computed victimization risk rates for groups defined by age, race and sex of respondents. By comparing these risk rates across domains and socio-demographic groups, we can determine the relative influence of activity and the composition of participants in a particular domain (Table 10).

Age of Respondent. One of the most consistent findings in the study of victimization is that younger persons are at greater risk than older persons. This general relationship holds across

B Leisure appears to be safer than our image of street crime would lead us to believe, but we must be careful here given the crudeness of our rate base. Almost everyone is included in the denominator of the leisure rate, but people spend substantially less time in leisure than in more obligatory activity. Consequently, the denominator of the leisure rate may be too large and therefore the rate may be too low.

domains, but its form varies by domain. Risk rises with age in some domains and falls more slowly in some than in others. Risk also varies for specific age groups across domains. For young persons the risk is greatest a school; for young adults the middle aged at home; for older adults risk is similar across domains; and for the elderly home and work are the most dangerous domains. When violent and property crime are viewed separately, there is even less regularity in the relationship between age and risk across domains. Only violence at work and at leisure and property crime at work show a consistent negative relationship between age and risk.

These patterns of risk across domains and age groups suggest a number of things. First, both age and domain seem to affect risk rates. This suggests that neither routine activities, nor the age composition of persons pursuing them are sufficient to explain differences in the victimization rate. Second, the risk of victimization for younger persons is substantially greater at school than it is in any other domain. If you remove victimizations at school for this youngest age group and substitute an average rate from the other domains, the victimization rate for this group would not be radically different from that of young and middle-aged adults. that leisure activity among the young is also highly agesegregated yet does not result in equally high rates of victimization, suggests that it is not simply the proximity of offending and victimization-prone persons that produces high risk rates. It may be that leisure is a much more discretionary You can choose your activity and your activity than school. companions in ways that minimize risk. In school you cannot. The high rates of violence at work and the persistence of those relatively high rates across age groups is consistent with this idea. When the risk of violence is due to one's occupation, avoidance is less possible regardless of the motivation to do so.

Sex of Victim. Males have higher risk of victimization than females in every domain except home where females have a 36% greater risk of victimization. The differences in risk between the sexes at work, school and leisure are quite small, ranging from 6 to 10%. These very small differences in risk across sex and domain suggest that most of the differences between risk for men and women are due to differential participation in activity domains, not greater risk within activities. The difference observed in the home domain suggest that women are at greater risk than men in what we have come to regard as the safest domain—home (Maxfield, 1987).

Race of Victim. There is no difference between whites and non-whites in the risk of being victimized generally, but Black respondents are at greater risk than Whites at home and at leisure. Whites have greater risk than Blacks at school and at work. These differences across domains may be due to the fact

that Blacks live and recreate in more dangerous areas than whites. There is no reason to believe, however, that Whites work and attend school at more dangerous places than Blacks. This distribution of risk is consistent with the differences between discretionary and obligatory activity discussed above. Blacks are at greater risk than whites in discretionary domains because segregation limits their ability to distance themselves from offenders. Whites on the other hand are attractive targets who have less ability to avoid potential offenders in obligatory domains.

Income. The risk of victimization decreases as income increases in the home, work and the leisure domains. Persons from higher income households have a greater risk at school than persons from lower income households. The relationship between income and victimization by domain is similar to that for race and domain-specific victimization and it seems to support the same interpretation. Higher income groups have the resources and freedom to distance themselves and their property from offenders in discretionary domains such as home and leisure. For these people, obligatory activity such as school and work increase the chance of victimization. For people who do not have the freedom or resources to choose safe places to live or recreate, the obligatory activities such as school and work are safer than being home or at leisure midst dense pools of potential offenders.

<u>Domain-Specific Opportunity Models.</u>

The foregoing sections examine risk across domains. The models discussed here explore risk within domains. Specifically, they predict victimization in a particular domain using indicators of opportunity concepts. Models are presented for three of the four domains defined above—home, work and leisure. The school domain is not included because the Victim Risk Supplement (VRS) was not administered to persons under 16 years of age and, therefore the bulk of students. Most of the additional information used to measure opportunity concepts in this analysis was obtain from the VRS. Since this was absent for the majority of students, an analysis of crime at school would not contribute much to the existing literature.

Victimization At Home.

Unlike the other activity domains examined in this report,

⁹ Chapter 9 of the full report deals with motor vehicle crime. This chapter is not discussed here due to space limitations and the fact that it is not entirely consistent with the domain-specific model logic.

the home domain has been the object of many empirical investigations, including the analyses presented above. Nonetheless, we hope that this analysis will contribute to our understanding of victimization in the home domain because of the additional information available from the segment analysis and from the VRS.

This analysis deals only with burglary and home larceny. Violence at home is omitted because the number of such crimes in the VRS is insufficient for multi-variate analysis. Moreover, violence at home involves a substantial amount of intra-familial crime for which opportunity models are not particularly appropriate (Morash, 1986).

Property victimization at home is predicted by an opportunity model in which risk is determined by proximity, attractiveness, exposure and guardianship. The specific indicators used are presented in Table 11. Moreover, this model assumes a hierarchical logic in target selection (Taylor and Gottfredson, 1986) in which indicators of opportunity models at higher levels of aggregation, e.g.neighborhood, are considered before indicators at lower levels of aggregation. i.e housing Consequently, attributes of these higher aggregates are entered into the model first followed by characteristics of lower level aggregates. Any attributes of higher level aggregates that are statistically significant are retained in the model when attributes of lower level aggregates are introduced. Attributes Separate models not found to be significant are not retained. were run for burglary and household larceny. The best fit models resulting from this process are presented in Tables 12 and 13.

Burglary. It seems clear from this analysis that the ecological variables included in our models are more powerful predictors of burglary than unit level variables. This is particularly true of neighborhood level factors. Community cohesion and community disorganization have reasonably strong and consistent relationships with the risk of burglary. Characteristics of the housing unit or the routine activity of household members are less strongly related to victimization risk. These findings suggest that in the target selection process characteristics of the neighborhood are more important than attributes of the particular housing unit (Sampson and Wooldredge, 1987).

It is less clear, however, why these particular attributes of neighborhoods should be salient in the choice of target. Cohesive neighborhoods may be avoided and disorganiz neighborhoods sought out because the chance of apprehension is perceived to be greater in the former and less in the latter. It is equally plausible to interpret these findings as the result of simple proximity.

The evidence available favors the proximity interpretation.

Data on the location of crimes and offender residence indicates that burglars commit the bulk of their crimes a short distance from their residence. This suggests that neighborhoods have high burglary rates because they are proximate to the residences of burglars. Moreover, the attributes of neighborhood that predict burglary most strongly are those that are also characteristics that the socialization of potential offenders. Socially cohesive areas are less often burglarized and households in socially disorganized areas have higher risk of burglary because the cohesive area produce fewer offenders and the disorganized areas produce more. The social-ecological processes that produce offenders also produce victims. Units are chosen for burglary because they are located in areas that produce dense pools of offenders.

The absence of significant interactions between variables at different levels of aggregation does not support hierarchical theories of target selection (Taylor and Gottfredson, 1986). According to these theories, offenders pursue a hierarchical selection process in which they first select large sections of metropolitan areas and then neighborhoods, followed by blocks and then specific units. If this were the case, then certain neighborhood characteristics would only be related to burglary in certain types of larger areas. Households in less cohesive neighborhoods become targets only in central cities, for example. Similarly, units only become targets in certain types of blocks. There were very few significant interactions in the models presented above and those observed occur between variables at the same level of aggregation and not across levels of aggregation.

The weak effects of income relative to community cohesion, community disorganization and the segment burglary rate raise some questions about assuming elaborate rational choice models of target selection. If household income is a useful measure of target attractiveness, then the weak (and negative) relationship between income and burglary observed in this analysis suggests that simple propinquity and not a minute weighing of costs and benefits drives the target selection process in the great bulk of burglaries. This is consistent with other work that has used different measures of proximity (Hough, 1987).

This is not to say that the target selection process for some relatively small proportion of burglaries does not involve an elaborate cost benefit calculus. The curvilinear relationship between burglary and income found in earlier suggests that the potential return from very high income households does figure in to the target selection process (see pp. above). Moreover, the interaction between income and area type found in above indicates that in areas not proximate to dense pools of offenders, attractiveness (as measured by income) does affect target selection. The vast bulk of burglaries, however, involve a less elaborate calculus. Moreover, to the extent that a

calculus takes place, the information incorporated in that equation is derived from and bounded by the areas that potential offenders frequent on a routine basis--their awareness space. These findings suggest that our understanding of the target selection process should start with the investigation of ecological processes and the life spaces of offenders rather than overly general and abstract models of the rational person.

This analysis confirms the importance of routine activity variables within opportunity theories. Specifically, this analysis uses more direct measures of activity out of the home and controls for the ecological factors that could account for observed relationship between activity and risk. When these factors are held constant, time out of the household has a significant if not particularly strong relationship to burglary.

The few physical design features included in this analysis do not influence the risk of burglary. The nature of land use (e.g., the existence of neighborhood nuisances) in the neighborhood is not significantly related to burglary. The number of units in the residential structure is also unrelated to the risk of victimization. The visibility and accessibility of the housing unit is not significantly related to burglary victimization. Finally, the use of protective devices such as dogs or locks does not affect the chance of being burglarized. There is no evidence here that differences in the physical design of areas or structures or attempts to harden targets has any effect on the risk of burglary.

Home Larceny. Unlike burglary where scholars have created elaborate models of target selection (Taylor and Gottfredson, 1986; Brantingham and Brantingham, 1978), larceny at home has been assumed to be the quintessential crime of opportunity. Property is taken from the home because it is lying around. In spite of the implicit consensus that household larceny is the quintessential crime of opportunity, we assume that the same general classes of factors affecting burglary may affect household larceny, although the specific factor within a class may affect one and not the other.

The results of the home larceny analysis are very similar to those for burglary. Attributes of the neighborhood and block are more important predictors of larceny at home than characteristics of the housing unit or household. Households in cohesive communities are less often victimized than those in less cohesive communities. Homes in disorganized communities are victimized more than those in socially organized communities. Households in blocks with histories of home larceny are more likely to be victims of home larceny in the future. Of the household level variables, only activity out of the house has a direct effect on home larceny. Households in which members were engaged in

extensive activities out of the home were more often victims of home larceny than households where members stayed home.

The model for home larceny departs from that of burglary in two respects. First, the presence of establishments that promote through traffic (neighborhood nuisances) has a significant positive relationship on home larceny, but it is not related to burglary. Second, single family homes in central cities are less often victims of larceny than we would expect from their location or structure, but housing structure has no effect on the risk of burglary.

The importance of neighborhood nuisances in predicting home larceny is consistent with the idea of home larceny as the quintessential crime of opportunity. The motivation to take goods from the home or adjacent property is presumably more generalized than the motivation to forcibly enter a home. Indeed, in some cases the ownership of household property is ambiguous and whether the taking of such property is theft is also ambiquous. When a tool is left on the lawn near the sidewalk, does it belong to the house adjacent to the lawn or has it been dropped by someone else? In the face of such ambiguity, a larger proportion of the population would be willing to take the tool than would be willing to take property when ownership is Presumably an even smaller proportion of the not in doubt. population would be unwilling to forcibly enter a house to take that property. Given the more generalized motivation to commit larceny as opposed to burglary, it is not surprising that the neighborhood factors that increase the flow of persons by property will increase the probability of theft, but not necessarily burglary.

The importance of housing structure in central city areas is also consistent with the image of home larceny as a function of the availability of goods unguarded. Multiple unit dwellings in the city tend to be larger than those in the suburbs and rural areas. There will be more large apartment buildings have more common areas than in other places. Apartment buildings have more common areas than two and three family houses. They usually have provision for storage far from the living unit. Property in these common areas and in distant storage areas is at greater risk than property in single family homes where ownership is more clearly demarcated and guardianship is easier. This may explain why single family homes are the object of less home larceny than multi-unit structures in the central city but not elsewhere.

Victimization at Work.

Work is often considered a dangerous activity, but usually risk at work is perceived as resulting from accidents or illness and not crime. The domain-specific victimization rates presented earlier, however, suggests that work is often the setting for

common law crimes in which employees are the victims of other employees or persons who are not co-woders. . But , it is unclear, from these rates, why work becomes a dangerous place.

Persons in the work force may be a self-selected group who would be victims regardless of their activity. It could also be that the higher victimization rates for working people are a function of the tasks performed on the job and that whoever performed those tasks would run similar risks.

Empirical tests of activity theory done to date provide little guidance in choosing among these competing explanations. The following analysis examines victimization at work in order to inform the debate over the factors that encourage victimization on the job. Specifically, we attempt to predict victimization at work using characteristics of workers, activity at work, attributes of the work environment, and security measures. characteristics of workers explains the distribution of victimization on the job, this would support the selective recruitment explanations. If activities on the job correlate more strongly with victimization, this would support routine activity explanations of the distribution of victimization in the labor force. The effects of security measures on the risk of victimization at work will indicate the extent to which such precautions can reduce risk.

Identifying the routine activity factors affecting risk of victimization at work requires the measurement of major concepts in the opportunity framework as they exist at work. The VRS included items that measure four key variables in routine activity theory: exposure, guardianship, proximity to offenders, and attractiveness. The specific operationalization of these variables and the measurement of victimization at work are described in Table 14.

Socio-demographic characteristics of workers, e.g. age, race and sex, are included in this analysis because they have been linked empirically to risk of victimization. Moreover, if this analysis is going to attribute causality either to the role or the occupant of that role, characteristics of the worker must be included.

The analysis proceeded in three stages. The first tested the relative influence of socio-demographic characteristics and routine activities on the risk of victimization. The second stage of analysis eliminates variables that were not significantly related to victimization in the first stage and introduces more detailed measures of opportunity variables, e.g., exposure, attractiveness, proximity to dense pools of offenders. In the third stage, we examine the effects of self protective measures on the risk of victimization when routine activity at work is held constant. Log linear modelling

techniques (Goodman, 1972) are used to test models of victimization at work.

Table 15 presents the models, likelihood ratios and effect parameters for the models that include demographic characteristics of respondents, exposure through routine activity at work, perceived dangerousness of the work place and victimization at work. The best-fit model for victimization at work (M9)includes only the direct effects of age, the composite exposure measure and perceived dangerousness on the risk of victimization. 10 This supports activity theories of victimization because exposure occasioned by routine activity at work affects risk of victimization at work even when the dangerousness of the area is held constant. The fact that demographic characteristics of victims--and particularly age--are not significantly related to victimization at work runs counter to findings from previous studies that examined victimization more generally (Cohen and Cantor, 1981; Gottfredson, 1984; Clarke, et al., 1985). This may have occurred because this study is restricted to persons in the labor force, thereby truncating the age distribution. A second possible reason for the insignificance of demographic characteristics of victims is that restricting the analysis to victimization at work reduces the importance of demographic characteristics for predicting risk.

In order to test the relative importance of these two factors in explaining the limited effects of demographic characteristics for victimization at work, we compared three models that used only age, race and sex of respondents to predict victimization. The first model included all victims and all victimizations. The second model was restricted to persons in the labor force, but still included all victimizations. The third model was restricted to persons in the labor force and to victimizations at work only.

Only the age of the victim had a statistically significant effect on victimization in <u>any</u> of the three models. In the model that includes all respondents and all victimizations, the effect of age is substantial. When the population is restricted to persons in the labor force but includes all victimizations, the effect of age is still large and statistically significant. The effect of age is dramatically reduced to the point that it is no longer statistically significant when victimization at work is used as the dependent variable. This suggests that the limited impact of age in predicting victimization at work is not due to the fact that the analysis is restricted to persons in the labor

¹⁰ Model 9 was selected as the best fit model over Model 10 because the difference between the chi-square values for the two models was statistically significant at the .05 level.

force, but because victimization at work is only weakly related to age.

Comparing these three models also indicates that the absence of a significant relationship between victimization and demographic characteristics of victims is <u>not</u> due to the fact that activities at work "explain" differences across types of victims. Age, race and sex of respondents in the labor force are not significantly related to victimization at work even when routine activity variables are not in the model.

When the individual indicators of opportunity concepts are used rather than the summary scale, more detail is available on determinants of risk (Table 16). Persons who work in areas proximate to potential offenders are more likely to be victimized than persons working in safer areas, regardless of their routine activity at work. Respondents with jobs that expose them to the public are more likely to be victimized than persons whose work makes them less accessible to the general public, regardless of the age of the person or the dangerousness of the area in which they work. Persons who are attractive targets of crime because they handle money as part of their job will be victimized more frequently than persons who do not carry money, all other things being equal. Finally, respondents who by virtue of the instability of their work place cannot exercise guardianship are at greater risk of victimization than persons who work at one location and seldom leave that location for business purposes.

When self-protective devices are introduced (Table 17), the overall fit of the model does not improve(LR Chi Square activity-related and protective practices = 7.96, d.f.=10, p>.5). This suggests that protective measures do not significantly affect the risk of victimization at work. Moreover, the relationships between victimization and the dangerousness of the work site, attractiveness, and guardianship and victimization, however, remain essentially the same.

These result suggest that victimization of employees by other employees or citizens while they are on the job is largely a function of the work environment, rather than the individual characteristics of workers. Moreover, prophylactic security measures such as guards or receptionist that do not fundamentally alter the nature of work are not associated with reduced risk of victimization on the job. These findings imply that efforts to reduce the risk of victimization on the job should focus on the social organization of work rather than superimposing security measures.

Victimization at Leisure

Victimization "at leisure" includes all victimizations that occur while pursuing activities that are more discretionary than

work or school and in locations other than the home. Activities such as going out in the evening to some form of entertainment or shopping would be considered "at leisure". Other activities such as local travel and commuting to work are also included. Il The discretionary nature of these leisure activities, as opposed to more "obligatory" activities such as work or school, can be a disadvantage for exploring victimization risk. It is difficult to characterize parsimoniously the wide variety of leisure activity. This, in turn, makes it more difficult to associate specific patterns of activity with victimization. The discretionary nature of leisure activity can also be an advantage in that people can more readily change this behavior to reduce the risk of victimization.

For both its advantages and disadvantages, crime at leisure may be a useful crime class. If victimization at leisure is the most difficult class of crime for which to measure routine activities, then it is important to isolate this domain so that research can focus on those domains in which routine activity can be operationalized adequately. Victimization at leisure is also a useful subject of study because the discretionary nature of leisure activity allows what we learn about factors affecting victimization at leisure to be more readily translated into action to reduce risk of victimization.

Routine activity theory explains victimization in terms of the roles and social structural position of people (Mayhew, et. al., 1975, Hindelang, et.al. 1978, Cohen and Felson, 1979). These factors determine the nature of the activity that people engage in on a routine basis which, in turn, influences the risk of victimization. Empirical investigations of personal victimization have begun by establishing the relationship between the demographic characteristics of victims (which indicate social structural position) and victimization. Routine activity variables are introduced into the analysis to see if they destroy or explain the observed relationship. This general logic will be followed here.

Studies of personal victimization have found differences among age, race and sex groupings. Men are victimized more than women, the young more than the old, and the minority more than the majority. These attributes of victims may be related to

¹¹ Commuting to work was not included in the work domain because the manner in which you commute is highly discretionary and crimes occurring on the way to work are not affected by the nature of the work environment. Including crimes that happen on the way to work in the category of work crimes would lessen the explanatory power of attributes of the work place. Grouping crimes occurring on the way to work in the leisure domain seemed more logical and desirable.

victimization that occurred at home, at work or at school. If this is the case, then these groups may not be at greater risk than others when pursuing leisure activities. In order to test this assertion, the age, race and sex of respondents were used to predict victimization at leisure. Several routine activity variables were introduced into the model of crime at leisure—the perceived dangerousness of the location, exposure (the frequency of leisure activities), and self protective measures. The perceived dangerousness of the areas in which leisure activities were pursued was measured by the respondent's assessment of the dangerousness of places where he or she shopped or went out for the evening. Exposure was measured by the respondent's estimate of the frequency with which he or she went shopping or went out for an evening. Self protective

¹² Respondents under 35 were considered young and those 35 or over were classified as old. All non-whites were considered members of minority groups. The sexes were distinguished in the usual way.

¹³ In order to determine the perceived safety of areas in which leisure activities were pursued, respondents were asked the following questions.

Do you think that the places you've visited or gone to for enjoyment are very safe from crime, fairly safe, fairly unsafe, or very unsafe?

Do you think that the places where you go to shop are very safe from crime, fairly safe, fairly unsafe, or very unsafe?

Responses of very safe were score as 1 and very unsafe scored as 5. Persons responding "Don't Know" were give a middle-point value of 3. The responses to these items were combined in an additive scale. The scale was dichotomized at the median to facilitate its use within the log linear models.

¹⁴ Exposure or frequency at leisure was measured by the following two question about the frequency of evenings out for fun and shopping.

During the last six months how often have you spent the evening out away from home for enjoyment? Everyday, at least once per week, at least once a month, less often, never.

During the last six months, how often have you gone shopping? Everyday, at least once a week, once a month, less often, never.

Responses were coded from 1 for everyday to 5 for never. The

practices at leisure were measured by questions asking the respondent if he or she avoided certain areas or carried a weapon for protection. $^{15}\,$

The relationships between demographic characteristics of victims and victimization at leisure are similar in some respects to those found for the more general category of personal crime. Younger people are more often victimized than older people and minority group members are victimized more frequently than whites. Surprisingly, there is no significant difference between males and females. Also, the group that we would expect to have the highest risk of victimization—young, minority, males— has a somewhat lower probability of victimization than we would expect given their characteristics.

Exposure and perceived dangerousness both influence the risk of victimization at leisure when the demographic characteristics of respondents are held constant (see Table 2). Persons who engage in leisure activity more frequently are more likely to be victimized at leisure. Those who pursue leisure activities in

scores on these two items were combined in a simple additive scale. The scale scores were dichotomized to facilitate their use in log linear models. Scores from 2 to 5 were considered high on exposure. Scores from 6 to 10 were considered low on exposure at leisure.

15 Two questions were asked of respondents in an effort to measure the self protective measures taken at leisure. One pertained to avoidance behavior.

In the past six months or so, have there been any times when you wanted to go somewhere but stayed at home instead because you thought it would be unsafe? Yes or No.

The other asked about carrying self protective devices.

When you go out, do you ever carry anything to protect yourself?

Yes or No.

Persons who responded yes were received a score of 1 and persons who responded "No" received a score of 0. The scores on the two items were added together to form a scale that ranged from 0 to 2. This scale was dichotomized with persons scoring 0 considered low on self protection and persons scoring 1 or 2 being considered as high on self protection.

places perceived to be dangerous are more likely to be victimized than persons recreating in safer areas. The effects of demographic characteristics are not substantially less than they were when activity variables were excluded from the model. This suggests that while the routine activity of persons at leisure can affect their risk of victimization, it does not explain the distribution of victimization across demographic groups.

The use of some sort of self protective measure--either avoidance or carrying a weapon-- has a strong positive relationship with the risk of victimization. Persons who engage in self-protective practices are more likely to experience victimization at leisure. This effect is much stronger than the effect of other activity variables or any demographic variables The effect of self-protective measures is the model. independent of the demographic characteristics of respondents or other activity variables. When the indicator of self-protective practices is introduced into the model, the effects of the other variables in the model remain essentially the same, except for perceived dangerousness. The effect of perceived dangerousness This occurs because persons who regard is reduced to zero. those places where they engage in leisure activities as dangerous are more likely to use some sort of protective measure.

This model is difficult to interpret largely because the temporal order of the variables involved is not clear. Perceptions of dangerousness and the use of self protective practices could be the result of victimization and not its cause. Alternatively, the use of self-protective practices may be a response to the perceived dangerousness of an area rather than a response to a recent victimization. Finally, persons who engage in routine self-protection may provoke victimization by preemptively protecting themselves when no actual threat has been made.

Precipitation, in the sense of preemptive or simultaneous attacks, does not seem to explain the relationship between selfprotective practices and victimization at leisure. violent crime at leisure admitted to taking preemptive action against attackers--attempting to defend themselves before or at the same time as the attack--in only 8% of the incidents There is virtually no difference in the use of reported. preemptive action between persons who engage in protective practices and those who do not. Engaging in self-protective practices also does not seem to be simply a response to recent victimization. The use of self-protection is less strongly related to recent victimization than it is too membership in high risk groups. Non-whites are more likely to engage in selfprotective practices than whites; those who engage in leisure activity use self-protective practices more than those who go out less frequently; and those who reside in central cities protect themselves more than persons living elsewhere. Men engage in

self-protective measures less frequently than women. 16 living in central cities engage in self-protective practices more than we would expect given their age and residence. All of these effects are stronger than that of recent victimization on the use of self protective practices. Finally, the fact that the effect of perceived dangerousness of leisure areas goes to zero when self-protection is introduced into the model supports the idea that the relationship between protection and victimization is due to the dangerousness of the areas in which people pursue leisure The positive relationship between self-protective practices and victimization at leisure is not causal. Both the use of self-protection and victimization are caused by the relative vulnerability of respondents. People who live in dangerous areas or are otherwise vulnerable to victimization both engage in self protection and are victimized at leisure.

When property crime at leisure is examined separately, exposure or time at leisure is positively related to victimization at leisure (see Table 18). Younger respondents are more often victimized at leisure than older persons and non-white respondents are more frequently victimized than white respondents. Also younger persons who frequently engage in leisure activities are less often victims than we would expect given their age and exposure. The perceived dangerousness of the places where leisure activities are pursued is not related to risk of property victimization at leisure.

The effects of frequency of leisure activities is the single largest effect in the model. The relationship between this variable and victimization is twice as strong as that for age or race of respondent. Routine activities (exposure), even crudely measured, are an important determinant of property victimization at leisure. It is equally important to note that perceived dangerousness of recreational areas (proximity) is not related to risk of property victimization at leisure. Together these results support the contention that property crime at leisure is ubiquitous and that the risk of property crime at leisure is not strongly patterned by the locations in which one pursues leisure activity.

When violent crime at leisure is examined separately, activity variables are important for predicting risk of victimization, but characteristics of victims are substantially more important (see Table 19). Frequency of leisure activity is positively related to violence at leisure. The perceived

¹⁶ Self defensive practices include both avoidance and the carrying of weapons. When the two aspects of self-protection are treated separately, men carry weapons more frequently than women and women admit to avoidance behavior more than men do.

dangerousness of the areas in which leisure activities are pursued is positively related to violent victimization at leisure. Younger persons are more at risk than older persons and non-whites are more likely to be the victims of violence than whites. Young, non-whites are particularly at risk of violence at leisure, but young, minority group males are at less risk than we would expect given their age, race and sex. This suggests that violent crime at leisure is less affected by the frequency of leisure activity than it is by other factors such as the characteristics of the person or the type of activity pursued. While property crime at leisure is ubiquitous, violent crime is not.

Central city residence has a strong positive effect on the risk of violent victimization when the demographic characteristics of the respondents and the frequency of leisure activity are held constant. This suggests that the dangerousness of the area in which leisure activities are pursued may be an important influence on the risk of violent victimization at leisure.

The introduction of central city residence into the model changes the effects of the other variables. The direct effect of race decreases which indicates that some of the effect of race was due to the fact that non-whites live in central cities. The effect of exposure increases when central city residence is included in the model. This suggests that central city residents who infrequently engage in leisure activity were often the victim of violent victimization at leisure. This suppressed the relationship between exposure and the risk of violent victimization. When central city residence was introduced into the model, the influence of the frequency of leisure activity increased.

Violent victimization is related to the frequency of leisure activity, but it is also strongly patterned by the dangerousness of the places where people recreate. It is more strongly related to the characteristics of victims. All of this suggests that either some crucial activity variables are left out of the model or that routine activity explanations are insufficient in themselves to explain well violent victimization at leisure.

Evaluating Domain-Specific Models

In an earlier section, we argued that in studies of broad classes of victimization such as violent or personal crime, routine activity variables cannot be well measured. This crude measurement introduces errors that understate the relationship between activity variables and victimization. If this is the case, then the relationship between activity variables and victimization should be stronger relative to structural variables

in domain-specific models than it is in the more general model. Moreover, this improvement in measuring independent variables coupled with the definition of a more homogeneous dependent variable should increase the explanatory power of domain-specific models relative to more general opportunity models.

In order to test these assertion, we compared the relative power of activity variables and structural variables in models of personal crime, crime at leisure and crime at work. Personal crime is a crime classification often used in studies of victimization that includes rape, robbery of persons, assault, personal larceny with contact and personal larceny without contact. Leisure crime, as described above, includes all crimes that occur while the victim is pursuing leisure activity away from home. Crimes at work include all crimes in the scope of the NCS that occur at the work site or while the victim is on the job.

The model of personal crime predicts victimization using the age, race and sex of the respondents as well as the extent of their activity out of the home. The model of leisure crime predicts victimization using the age, race and sex of respondents and the frequency of their leisure activity. The model of crime at work predicts victimization at work using the age of the respondent, activities at work and attributes of the work environment. This was the best fit model identified in previous analyses of crime at work (Lynch, 1987).

Comparing these three models will provide a test of the advantages of domain-specific models. The model of personal crime attempts to explain a large and heterogeneous class of crime that does not differentiate crimes according to activity of the victim at the time of the incident. The leisure crime model attempts to explain a class of crime defined by activity at the time of the incident. The independent variables in this model are essentially the same as those used in the personal crime model, but the activity variable is measured by questions pertaining only to leisure activities. The work model restricts the dependent variable to crime in a specific domain and it also takes full advantage of the domain approach by including detailed

¹⁷ For a description of the specific variables and codes used in the prediction of personal crime see Appendix A.

¹⁸ For a description of the specific variables and codes used in the leisure crime analysis see Appendix A.

¹⁹ For a description of the specific variables and codes used in the work crime analysis, see Appendix A.

information on the work environment.²⁰ If our assertions are correct, the effects of activity variables should be greater than structural variables in the domain-specific models relative to the personal crime model. Moreover, the effects of activity variables relative to structural variables should be strongest in the work domain because we were able to more fully exploit the advantages of the domain approach.

The effect parameters and standard values for these models are presented in Table 20. In the personal crime model, the standard value for the age parameter is about 33% greater than that for the exposure parameter. In the crime at leisure model the combined standard values for age and race are about 11% less than that for exposure. In the crimes at work model, the standard value for the age effect is 14% that of the combined standard values for the activity variables—exposure, mobility, perceived dangerousness, and handling money. Indeed, the standard value for any of the activity variables in the work model are greater than the standard value for age. These results seem to support the idea that domain specific models of victimization will permit better measurement of activity variables such that their effects are not underestimated relative to structural variables.

These results must be viewed cautiously. The work and leisure crime models were the product of searches for the best-fit model from among a number of alternatives. The same is not true for the personal crime model. It is conceivable that a better fitting model could be developed for personal crime in which activity variables would have more substantial effects than structural variables. Nonetheless, the variables included in the personal crime model include many of the measures found to be important predictors of victimization in previous studies of personal crime (Gottfredson, 1984; Sampson and Wooldrege, 1987). While these results are not definitive, they do support our contention that domain-specific models permit better measurement of routine activity concepts and that this improved measurement will result in more significant effects of activity variables on the risk of victimization.

The improvements in explanatory power that we can expect from domain-specific models can be tested by comparing the explanatory power of the general and domain-specific models presented in the previous section. If our assertions are accurate, then models of crime at work or crime at leisure should

Recall that the work model presented here initially included the age, race, and sex of respondents, but only retained age because these other socio-demographic variables were not significantly related to victimization at work.

be more predictive of victimization than that for personal crimes.

Assessing the explanatory power of general and domainspecific models of victimization is complicated by the nature of victimization. First, victimization, as defined in this analysis, a dichotomous event. Moreover, the distribution of victimization is highly skewed. In any reasonable period of time only a small proportion of the population becomes a victim of Standard ordinary least squares regression offers the most straightforward measure of explanatory power--R2--, but this statistic is not particularly appropriate for dichotomous variables with highly skewed distributions. Some would argue that OLS regression is robust enough to yield valid results with dichotomous dependent variables. Alternatively, logistic regression and log linear models are better suited to the study of dichotomous dependent variables and can provide a measure of explained variance with a little massaging(Goodman, 1971). much can be done, in either regression or logistic regression, about the problems posed by a highly skewed distribution. Finally, simple proportionate reduction in error statistics, such as Goodman and Kruskal's Tau, indicate the improvement in prediction which can be interpreted in the same way as explained This approach to determining explanatory power may be variance. more desirable than regression based-methods because it does not rely upon the concept of variance. Moreover, this statistic is not seriously affected by skews in the dependent variable. method requires the categorization of independent variables, however, and this may limit the explanatory power of particular independent variables.

Given the special problems posed by a highly skewed distribution on a dichotomous dependent variable, two approaches were taken to estimating the explanatory power of general and domain specific models. The first was Ordinary Least Squares (OLS) regression. Regression models were run with the independent variables coded as dichotomies and with the independent variables in more continuous form. The resulting Rsquares were used as measures of explanatory power. The second method involved the computation of Tau for a cross tabulation of a combination of all independent variables with the dependent variable--victimization. The two approaches yielded somewhat different results.(table 21)

The regression results indicate that the proportion of explained variance in the model of personal crime is essentially the same as that for the model predicting crime at work, when the dichotomized versions of the independent variables is used. When more continuous measures of the independent variables are used, the R-squared is greater in the model of personal crime than it is for either the leisure or work models. In contrast, the Tau for the personal crime model is essentially the same as the Tau

for the leisure crime model and the Tau for the work model is twice that of the other two models.

The inconsistency of these results indicates that more work must be done on this issue of explanatory power when dealing with rare events like victimization. We must know more about the appropriate measures of explanatory or predictive power that are appropriate for use with highly skewed, dichotomous dependent variables. Alternatively, we may want to think of ways of obtaining accurate data on victimization that is not highly skewed. This could involve accumulation in rotating panel designs over time or the use of true longitudinal surveys.

The results presented here offer some tentative support for the greater explanatory power of domain-specific models. While the leisure crime model does not do any better predicting leisure victimization than the personal crime model does predicting personal crime, the work crime model does substantially better than personal crime model. This is not surprising, given the superiority of the work model as an example of a domain-specific Work is a reasonably clear and definable set of activities that can be characterized clearly. Leisure on the other hand covers a wider variety of activities that are difficult to characterize. Consequently, the internal homogeneity of the work domain is greater than that of the leisure domain. This should increase the explanatory power of the work model relative to the leisure model. Moreover, the VRS contained a great deal more specific information on the work domain than it did on the leisure domain. This resulted in greater precision in the measurement of the independent variables in the work domain relative to the leisure domain. Consequently, I would give more weight to the performance of the work model as an example of the gains in explanatory power than can be achieved by domain-specific models. In so doing, we must conclude that domain-specific models do increase the explanatory power of routine activity models.

Summary

This analysis provides some support for the advantages of domain-specific models of victimization relative to more general models of victimization. Classifying crimes by activity domains offers a fresh and enlightening perspective on victimization. changes our view of what is a safe or dangerous place or a risky It sheds new light on why certain relationships between victimization and structural factors such as the age effect should persist. Domain specific approaches also seem to permit better conceptualization and measurement of routine activity concepts. This, in turn, facilitates identifying more accurately the influence of routine activity variables on the risk of victimization. There is also some evidence that domainspecific models, correctly implemented, do improve the overall explanatory power of routine activity models.

This analysis also indicates some of the limitations of domain-specific models. First, although domain-specific models of victimization have somewhat more explanatory power than more general models, our ability to predict who will be a victim is still extremely limited. At best the models presented here still extremely limited. At best the models presented here permit only a 2% improvement in our ability to predict victimization. This is not impressive. It is not clear exactly how well we could expect to predict victimization given the extreme skew in the distribution. More must be done to improve our ability to predict victimization. While improving our measurement of independent variables will undoubtibly help, we must also look for ways to compensate for the fact that victimization is an extremely rare event. Second, it seems clear that the leisure domain is too inclusive to be useful. must be made to subdivided this domain into more homogeneous domains. Perhaps shopping activity should be separated from "going out for an evening and both of these separated from commuting. Also, a neighborhood domain should be added to our typology of domains. This would include all activity not in other domains that occurs within a mile or less of the home. substantial number of incidents seem to occur in this location.

As a strategy for building activity theory, domain-specific models is not well defined. This analysis suggests that it has potential and is worth further attention. It also suggests ways in which this strategy could be refined.

Conclusions

This project was design to begin to bridge the gap between opportunity theories of victimization risk and policy. Opportunity theory has promise for guiding efforts to reduce victimization, but it is too abstract to have immediate policy implications. By introducing two methodological innovations—multi-level models and domain-specific models—we attempted to m a k e t h addition, we hoped to be able to evaluate these innovations as general strategies for building an empirically based opportunity theory. The implications of our work for opportunity theory and policy are presented below.

Implications for General Opportunity Theory

It is clear from our results that the basic opportunity model must be refined. Specifically, the concept of proximity should be given preeminence in the opportunity framework and subdimensions of most of the other concepts--guardianship, attractiveness, and exposure--should be identified. Models should be explicitly multi-level incorporating measures of activity concepts at various levels of aggregation rather than emphasizing only the individual-level.

The preeminence of proximity in the opportunity framework is dictated by both logic and the results of empirical tests. opportunity theory, crime events require the presence of victim and offender. If these principals are not proximate, then attractiveness, guardianship and exposure will not discriminate between victims and non-victims. Consequently, proximity should come first in the opportunity framework. The empirical results presented above also support the overriding importance of proximity relative to other opportunity concepts. Measures of the proximity of dense pools of offenders are the most powerful predictors of victimization in virtually every model tested. Indicators of proximity were the most powerful discriminators between high and low crime areas in the areal typology analysis. When the areal typology was used as an indicator of proximity in the multi-level analysis, it had a strong relationship with victimization. There were also strong interactions between areal type and other opportunity concepts such that exposure, attractiveness and guardianship were related to risk differently in different types of areas. Finally, measures of proximity were powerful predictors of victimization in most of the domainspecific analyses.

Constructing opportunity models for various types of crime in various domains made apparent the need to define subdimensions of opportunity concepts. Other wise, the general opportunity framework provides inadequate guidance for empirical The concept proximity, for example, should be subdivided into two dimensions -- associations and simple propinquity. Victims and offenders can be brought together simply by being close geographically or their can be a pre-existing relationship between them that occasions interaction. This relationship could be kinsman, classmate, or co-worker. This distinction is useful in that propinquity suggests proximity through happenstance and interaction among strangers, while association indicates a seeking out and a greater degree vulnerability. Presumably, attractiveness, exposure and guardianship would have different implications for risk in the former than the latter. Guardianship can also be sub divided into dimensions. distinction should be made between animate (persons) and inanimate (alarms) guardians. In the models of crime at home, the presence of persons in the home had a consistent negative relationship with victimization, while alarms, locks, and other inanimate guards had no effect. The same was true in the work Exposure has been divided into a visibility and an accessibility dimension. Some provision most be made for familiarity or knowledge of a target that does not come from visibility.

The predictive power of neighborhood and block characteristics in all of our empirical models underscores the importance of including ecological context in opportunity models.

Residential area type is a more powerful predictor of burglary and home larceny than the characteristics of individuals when the full NCS sample is used. When the more detailed data in the VRS are used, characteristics of the block and neighborhood are more strongly related to victimization at home than attributes of housing units or households. The segment crime rate, community cohesion and community disorganization have substantial effects on the risk of burglary. Similarly, for home larceny, segment larceny rate, community cohesion, and the presence of establishments that draw persons to the community are significantly related to risk of home larceny. In the domainspecific analyses, attributes of the work area and the leisure area are strongly related to victimization risk. Although the measurement of opportunity concepts at various levels of aggregation is not simple, these analyses suggest that it is essential that both ecological and individual level variables be included in conceptual and empirical models.

The various empirical models tested in this study suggest that it is unwise to employ a single opportunity model to all types of crime. Within the home domain, the factors affecting burglary are different from those influencing home larceny. Proximity seems to be more consequential for predicting burglary than it does for predicting home larceny. While the type of residential area seems to influence the probability of victimization generally, area type interacts with individual level factors for burglary, but not for home larceny. So the effect of exposure or guardianship on risk will vary with the type of area for burglary, but not for home larceny. Similarly, both burglary and home larceny will occur more in socially disorganized areas than in more organized areas, but the amount of through traffic in an area will increase the risk of home larceny, but not the risk of burglary. Also, multiple units are less susceptible to burglary, but more at risk of home larceny than single family structures. In sum, the motivation to commit burglary is highly clustered, so proximity is a major determinant The motivation to engage in home larceny is more ubiquitous and the occurrence of home larceny is affected more by other opportunity concepts such as exposure or attractiveness.

The differences across domain-specific opportunity models further supports the need to construct crime-specific models of victimizations. The risk of crime at work is influenced exclusively by characteristics of the work environment. Sociodemographic characteristics of workers do not affect risk at work. In contrast, characteristics of persons are strongly related to risk of victimization at leisure. Exposure and proximity at leisure do affect risk at leisure, but not to the extent that they do at work. Similarly, within the leisure domain, exposure and proximity are much more powerful predictors of property victimization than characteristics of victims are. The reverse is true for violent crimes at leisure. It is unclear

at this point why these differences occur. It may be that in the work environment, the nature of the work role supercedes the proclivities of the employee and determines risk, while in more discretionary activity, like leisure, the predispositions of the person are less constrained and, therefore, influence risk. It could also be, that the measures of opportunity concepts (and particularly routine activities) are better at leisure than at work. Whatever the reason, it seems clear that trying to explain all of these types of crime with a single empirical model, is undesirable. It would obscure real and important differences in the effects of opportunity concepts and inhibit our understanding of the processes leading to victimization.

Implications for Multi-level and Domain-Specific Models As Strategies for Building Opportunity Theory

Given the importance of multi-level opportunity models for understanding the distribution of victimization risk, it is essential that we find methods for obtaining data on individuals and ecological aggregates. The segment aggregation approach presented here seems to be a viable way of obtaining the information necessary for multi-level models. The fact that the between segment variation in victimization risk is substantial confirms the utility of using segment as an ecological unit in multi-level models of victimization risk. This is not to say that segment is the only or the best ecological unit for the study of all types of crime, but it is one way to obtain ecological data without adversely affecting national estimates of victimization.

Domain-specific models also show some promise as a strategy for building an empirically based opportunity theory. domains used here seem to include the vast majority of all victimization. Additional domains could be added to make the classification of domains exhaustive. Domains also seem to refer to very distinct contexts for victimization. The risk of victimization differs substantially across domains. Moreover. the empirical models used to predict risk are quite different across domains. All of this suggests that differentiating crimes and contexts by domain is useful. There is some evidence that the measurement of opportunity concepts is better in domainspecific models than it is in more general models of Routine activity measures of opportunity victimization risk. concepts are more strongly related to victimization in domainspecific models than they are in more general models. results seem to justify additional work on domain-specific models of victimization.

The promise of multi-level and domain-specific models suggests that future research should further these strategies for testing and building opportunity theory. Additional information should be obtained on segments and other ecological aggregates to be used in multi-level models of victimization risk. Existing information should be used more extensively to indicate the nature of high crime segments. More information should be obtained on victimization in domains other than work in order to provide more adequate tests of a opportunity models in those domains.

These two directions for additional research should be pursued first with existing data bases and then with modest new collections where appropriate. The potential of the NCS for exploring multi-level models has not been exhausted. The areal analysis presented here could be done using a more continuous as opposed to typological approach to determine what makes areas dangerous and how area affects risk of victimization. It may be possible to identify and combine adjacent segments in the NCS to explore the effect of units larger than segment on the risk of victimization. Supplements to the NCS can be used to explore the school and leisure domains in the way that the VRS was used for work and home.

Implications for Policy

Opportunity theory cannot serve as a specific guide to policy until it becomes much less general and abstract. this project has moved opportunity theory in that direct, it cannot be used to prescribe crime control efforts. The principal benefit of this work is the identification of research that would further reduce the gap between theory and prescription. Nonetheless, some of the findings presented in this report can be used to suggest general directions for crime control efforts. First, these analyses demonstrate that victimization is highly clustered geographically and that the same types of areas produce offenders and victims. This is not consistent with crime control strategies that assume that victims and offenders come from radically different populations. Strategies that assume a defended community, for example, in which residents are put upon by external forces and groups is not applicable to the vast majority of victimization in residential areas. It appears that most victims are probably victimized by their neighbors. the fact that victims are highly clustered geographically suggests that crime control should take an explicitly ecological focus. Efforts should be made to make areas with high victim and offender populations safer. This is a very different emphasis from the mass-marketing campaigns currently used to promote crime reduction through self protection. Third, domain-specific models indicate that a substantial proportion of victimization occurs not in the residential community, but a school, at work and at

leisure. While school crime receives a great deal of attention from both the law enforcement and education industry, the same is not true of victimization at work and at leisure. Thinking about crime control efforts should focus on these neglected domains. They seem ripe for cooperative efforts involving both the public and private sectors. While opportunity theory cannot yet be used to prescribe minutely crime control policy, this research can suggest to policy makers and interested citizens where they might most fruitfully turn their creative energies to reduce risk.

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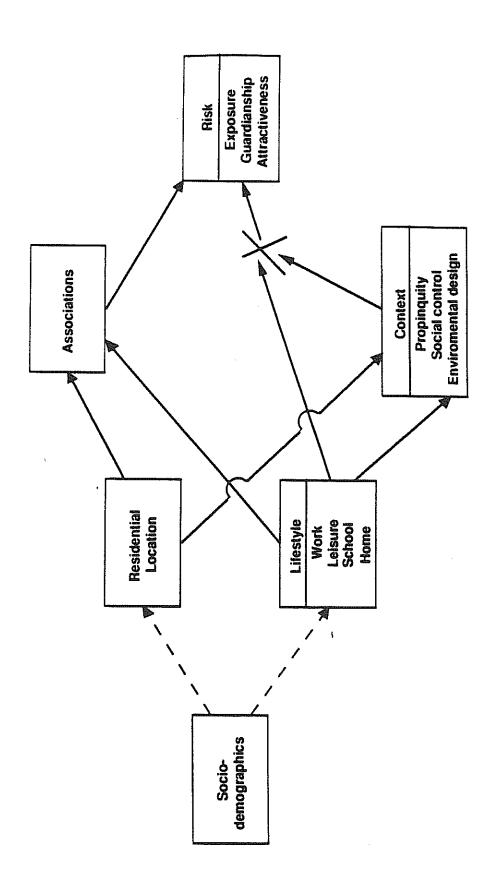


Figure 1 Modified Opportunity Model Predicting Individual Victimization Risk

Table 1. Median crime rates for segments by type of area and type of crime (address segments only)

I ype	of	Area

	<u>Violent</u>	Property	Low
Serious Violence	.056	0	0
Personal Property	.093	.060	.022
Burglary	.087	.071	0
Home Larceny	.118	.125	0
Number of segments	136	419	958

Table 2. Variables used in canonical discriminant analysis predicting area types

Proximity to motivated offenders

% of respondents that are nonwhite
% of households with incomes below \$5,000
% of respondents that are unemployed
Fear of crime within neighborhood
Fear of crime within shopping neighborhood
Fear of crime within leisure activity neighborhood
Number of offenders coming from outside neighborhood
Central City
Suburban Area

Guardianship

% of households owned by occupants % of single parent families Presence of a neighborhood watch % of single family homes % of structures with 10+ units Presence of protect devices in house

Attractiveness/Exposure

% of population 18-24
Presence of commercial/public building
Mean household income
% of persons in home-based activities
Average number of times respondents go outside the home during the week
% of population less than 12 years old

Table 3. Canonical structure coefficients for discriminant analysis predicting membership into three area crime types using aggregated segment characteristics

	Canonical Variate		
Independent Variables	1 .	2	
% Single Parent	.38	12	
% 10+ Units structures	.18	48	
Mean Family Income	33	.51	
% Unemployed	.29	27	
% Units owned	48	.48	
% 18-24	.49	19	
% Non-white	.37	26	
Neighborhood Watch	35	.20	
Offender From Neighborhood	55	21	
Frequency out for Evening	.01	19	
Fear of Leisure Neighborhood	.46	06	
Fear of Shopping Neighborhood	.32	04	
Fear of Residential Neighborhood	.73	.03	
Protection	04	.54	
Squared Canonical Correlation	.19*	.03*	
Class Means			
Hi Violence	1.07	41	
Hi Property Lo crime	.45	.22	
LU CI IME	35	04	

Table 4. Best fitting log-linear models predicting Burglary (B) and Household larceny (L) using selected combinations of Age (A), Marital Status (M), Race (R), Income (I) and Number Of Units In The Structure (U) by whether Area Type (T) is included

A. Burglary

M	odel including age,			Inclus	ion of	Area Type			
	artial status and:	Without Area Type	<u>L</u> ²	<u>Df</u>	<u>P</u>	With Area Type	<u>L</u> ²	<u>Df</u>	<u>P</u>
1.	Race	AB,MB,RB,AMB	4	7	.78	AB,MB,TB,AMB, ATB,MTB	36	41	.70
2.	Income	AB,MB,IB,AIB	11	11	.44	AB,MB,IB,TB, MTB,ATB,ITB	61	68	.72
3.	# Of Units	AB,MB,UB,AMB, UMB	12	12	.40	AB,MB,UB,TB, AMB,ATB,UMB	70	72	.54
		B. Hou	seholo	Larce	env				
1.	Race	AL,ML,RL,AML	8	7	.34	AL,ML,TL	55	56	.51
2.	Income	AL,IL,AIL	12	12	.52	AL,IL,ML,TL, AIL,MTL	70	77	.71
3.	# Of Units	AL,ML,UL,AML	17	14	.25	AL,ML,TL,UL, AML	90	83	.27

^{*}Elimination of any interaction from a particular model will result in a statistically significant jump (p<.10) in the Chi-square. All models include the 3-way interaction with the predictor variables.

Table 5. Additive Log-linear Parameters For Model Predicting Burglary Victimization With Age Of Head, Marital Status Of Head, Area Type And Income

2-Way Interactions With Burglary

3-Way Interactions With Burglary

		_	
Λ.	rea	_1 ypc	-
α	1 Ca	1 V 131	

		Violer	nt Property	<u>Low</u>	Rural
Age					
18-29 30-49 50-64 65+	.14 ¹ .05 07 ² 12 ²	12 ² 01 02 .15	05 .02 .12 ² 09	.14 ² .00 11 ² 04	.04 01 .00 03
Marital Status					
Married Not Married	10 ¹ .10 ¹	.04 04	.07 ² 07 ²	.00 .00	11 ¹ .11 ¹
<u>Area Type</u>					
Violent Property Low Rural	.40 ¹ .18 ¹ 42 ¹ 16 ¹				
<u>Income</u>					
0-9999 10000-29999 30000+	01 071 .08 ²	.07 07 .00	.09 ² .00 09	02 .02 .00	14 ¹ .04 .10

 $l_{t-value > 1.96}$

 $²_{t-value > 1.25}$

Table 6. Additive Log-linear Parameters For Model Predicting Burglary Victimization With Age Of Head, Marital Status Of Head, Area Type And Number Of Housing Units In The Structure

	2-Way Interactions With Burglary	3-Way Interactions With Burglary						
		<u>Mari</u>		Area Type				
		Married	Not Married	<u>Violent</u>	Property	Low	Rural	
Age								
18-29 30-49 50-64 65+	.15 ¹ .06 10 ² 11 ²	05 ² 04 .06 .03	.05 ² .04 06 03	10 ² 02 03 .15	06 .01 .12 ² 06	.10 ² .02 08 05	.07 01 02 04	
Marital Status								
Married Not Married	06 .06							
Area Type								
Violent Property Low Rural	.40 ¹ .21 ¹ 42 ¹ 20 ¹		·					
# of Units								
1 2-4 5+	.02 .05 06							

 $l_{t-value > 1.96}$

 $²_{t-value > 1.25}$

Table 7. Additive Log-linear Parameters For Model Predicting Home Larceny Victimization With Age Of Head, Marital Status Of Head, Area Type And Income

	2-Way Interactions With Larceny	3-Way Interactions With			tions With	With Larceny		
			<u>Income</u>		Area Type			
		0-9999	10000-29999	<u> 30000+</u>	<u>Violent</u>	Property	Low	Rural
Age								
18-29 30-49 50-64 65+	.16 ¹ .06 05 16 ¹	.08 ² .08 ² .00 16 ¹	08 02 .00 .10 ¹	.00 06 .00 .06				
Marital Status								
Married Not Married	.04 ² 04 ²				02 .02	.03 03	.04 04	05 .05
Area Type								
Violent Property Low Rural	.26 ¹ .29 ¹ 31 ¹ 25 ¹							
Income								
0-9999 10000-29999 30000+	05 ² .04 .00							

¹ t value > 1.96

 $²_{\rm t\ value} > 1.25$

Table 8. Additive Log-linear Parameters For Model Predicting Home Larceny Victimization With Age Of Head, Marital Status Of Head, Area Type And Number Of Housing Units In The Structure

	2-Way Interactions With Larceny	3-Way Interactions With Large	
		<u>Marit</u>	al Status
•		<u>Married</u>	Not Married
Age			
18-29 30-49 50-64 65+	.17 ¹ .10 ¹ 05 22 ¹	03 03 .02 .05	.03 .03 02 05
Marital Status			
Married Not Married	.06 ¹ 06 ¹		
Area Type			
Violent Property Low Rural	.29 l .30 l 30 l 29 l		
# of Units			<u>.</u>
1 2-4 5+	.03 .06 ² 09 ²		

 $l_{t-value > 1.96}$

 $²_{\rm t-value} > 1.25$

Table 9: Victimization Counts and Percents by Domain

Domain	Number	各	% (excluding unclassified)
At Home	839	29.9	38.5
At Work	447	15.9	20.5
At School	323	11.3	14.8
At Leisure	568	20.2	26.1
Not Classified	629	22.7	••• ••

Table 10: Person-based Victimization Rates by Type of Crime, Domain and Socio-demographic Characteristics of Victims.

Domain

	lctim Type	Home	Work	School	Leisure
All	All	.033	.037	.066	.023
Property	All	.03	.026	.056	.015
Violence	All	.003	.011	.011	.008
All	Age				
	12-24 25-35 36-45 46-55 56 +	.029 .047 .046 .026	.053 .043 .036 .026	.077 .014 .06 .029	.032 .033 .019 .022
Violence	Age	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,			
	12-24 25-35 36-45 46-55 56 +	.002 .005 .002 .003	.017 .015 .009 .005	.014 .0 .005 .0	.016 .01 .004 .002
Property	Age			~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~	~~~~~~
	12-24 25-35 36-45 46-55 56+	.027 .042 .043 .023	.036 .028 .028 .021	.064 .014 .059 .029	.016 .023 .015 .011
All	Sex				=======
	Female Male	.038	.037	.064	.021
Violence	Sex Female Male	.004	.007	.009	.005 .01
Property	Sex				
	Female Male	.034 .026	.03 .025	.056 .055	.016 .014

Table 10: Person-based Victimization Rates by Type of Crime,
Domain and Socio-demographic Characteristics of
Victims.(Cont)

	(00110)	Home	Work	School	Leisure
All	Race				
	White Non-white *	.032	.038	.068	.022 .027
Violent	White	.003	.011	010	
	Non-white	.003	.011	.012 .005	.007 .01
Property	**1				
=======	White Non-white	.029 .04	.028 .019	.057 .05	.015
All	Income				
	<7500 7501 to 17500	.056 .038	.047	.034	.032
	17500+	.026	.036	.075	.020
Violence	17500				
	<7500 7501 to 17500	.008	.012 .011	.004	.014 .009
	17500+ 	.001	.011	.012	.005
Property					
	<7500	.049	.035	.03	.018
	7501 to 17500	.034	.028	.05	.013
	2,000				

Table 11: Concepts and Indicators in the General Home Crime Model by Level of Analaysis

<u>Level of</u> <u>Analysis</u>	<u>Variable</u>	Indicator
Large Area	Proximity to Offenders	Central City Residence
Neighborhood	Community Disorganization	Interviewer Observation of Litter, etc. (Personal In- terviews only)
	Community Cohesion	Outsiders commit crime and watching homes
	Traffic Flow	Presence of Neighborhood Nuisances
	Attractiveness	Household Income
Block	Proximity to Offenders	Segment Crime Rates
Housing Unit	Accessibility	Visibility and Distance from Road (Personal interviews only)
	۱,	Single Family Structure
Guardia	External Security Measures (personal interviews only)	

Internal Security Measures (Personal Interviews only)

Internal Security

Household

Guardianship

Time Out of

Home

Household Size

Table 12: Log Linear Model Predicting Burglary Using Community Cohesion (H), Activity Out of the Home (A), Segment Larceny Rate (S), and Household Security (P): Full VRS Sample

				<u>Model</u>	<u>.</u>			<u>Chi-Sq</u>	DF	<u>P</u>
Ml				HASPE	3			0	0	0
M2		HASB	НА	PB HSP	B AS	PB		.38	1	>.5
МЗ	HAB	HSB	HPB	HAPB	ASB	APB	SPB	5.16	5	.39
M4			НВ	AB SE	PB			13.11	11	.28
M5		H A	S	Р В				183.4	15	.00

<u>Variables</u>	<u>Lambda</u>	Std. Val.
Activity	.07	2.21
Segment Larceny	.283	8.92
Community Cohesion	19	5.9
Home Security	.042	1.32

Table 13: Log Linear Model Predicting Burglary Using Unit Protection(P), Segment Burglary Rate (S), Community Cohesion (H), Community Disorganization (D):Personal Interviews Only

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<u>Variables</u>	<u>Lambda</u>	Std. Val.
Segment Burglary Rate	.322	5.79
Community Cohesion	198	-3.55
Community Disorganization	.127	2.29
Two Variable interactions		
Unit Protection X Community Cohesion	.146	2.6
Unit Protection X Community Disorg.	.112	2.01
Three Variable Interactions		
Unit Protection X Segment Burglary Rate X Community Cohesion	.156	2.8

Table 14: Log Linear Model Predicting Home Larceny (L) Using Central City Residence (C), Neighborhood Nuisance (N), Community Cohesion (H), Segment Larceny Rate (S) and Single Family Home (F): Full VRS Sample

	<u>Models</u>	<u>Chi-Sq</u>	<u>DF</u>	P
Ml	CNHSFL	0	0	0
M2	CNHSL CNHFL CNSFL CHSFL NSHFL	6.04	2	.048
МЗ	CNHL CNSL CNFL CSFL CHSL CHFL NHSL NHFL NSFL HNFL HSFL	12.9	9	.167
M4	CNL CHL CSL CFL NHL NSL NFL HFL SFL HSL	16.65	16	.40
M5	CNL HL FL SL	25.32	25	. 44
M 6	CL NL HL SL FL	40.68	26	.03
M7	C N H S F L	300.64	31	.00

Effect Parameters and Standard Values for the Best Fit Model--M5

<u>Variables</u>	<u>Lambda</u>	Std. Val.				
Neighborhood Nuisance	.108	3.2				
Community Cohesion	096	-2.84				
Segment Larceny Rate	.295	9.7				
Two Variable Interactions						
Single Family Home X Central City Reside	.084 ence	-2.49				

Table 15: Log Linear Model predicting Home Larceny (L) Using Home Security (G), Central City Residence (C), Neighborhood Nuisance (N), Segment Larceny Rates (S), Community Cohesion(H):Full VRS Sample

	<u>Models</u>	Chi-Sq	<u>DF</u>	<u>P</u>
M1	GCNSHL	0	0	0
M2	GCNSL GCNHL GCSHL GNSHL CNSHL	1.84	1	.17
МЗ	GSNL GCSL GCHL GNSL GNHL GSHL CNSL CNHL NSHL	10.4	9	.31
M4	GCL GNL GSL GHL CNL CSL CHL NSL NHL SHL	19.2	16	.25
M5	GL CL NL SL HL	32.4	26	.18
M 6	G C N S H L	316.55	31	.00

<u>Variables</u>	Lambda	Std. Val.
Central City Residence	.064	2.12
Neighborhood Nuisance	.104	3.4
Segment Larceny Rate	.31	10.3
Community Cohesion	079	-2.6

Table 16: Log Linear Models of Home Larceny (L) Using Activity Out of Home (A), Segment Larceny Rate (S), Neighborhood Nuisance (N), Community Cohesion (H) and Community Disorganization (D):Personal Interviews Only

	<u>Models</u>	<u>Chi-Sq</u>	<u>DF</u>	<u>P</u>
Ml	ASNHDL	0	0	0
M2	ASNHL ASNDL ASHDL ANHDL SNHDL	.17	2	>.5
МЗ	ASNL ASHL ASDL ANHL ANDL SNHL SNDL SHDL NHDL	5.4	10	>.5
M4	ASL ANL AHL ADL SNL SHL SDL NHL NDL HDL	8.3	16	>.5
M5	AL SL NL HL DL	15.79	2.6	>.5
M 6	A S N H D L	135.4	31	.00

<u>Variables</u>	<u>Lambda</u>	Std.Val.
Activity Out of Home	.072	2.4
Segment Larceny Rate	.15	5.2
Neighborhood Nuisance	.10	3.4
Community Cohesion	08	-2.76
Community Disorganization	.09	3.1

Table 17: Log Linear Models of Home Larceny (L) Using Housing Unit Security (U), Segment Larceny Rate (S), Neighborhood Nuisance (N), Community Cohesion (H) and Community Disorganization (D): Personal Interviews Only

	<u>Models</u>	<u>Chi-Sq</u>	<u>DF</u>	<u>P</u>
Ml	USNHDL	0	0	0
M2	USNHL USNDL USHDL UNHDL SNHDL	.23	2	>.5
М3	USNL USHL USDL UNHL UNDL SNHL SNDL SHDL NHDL	11.9	10	.29
M4	USL UNL UHL UDL SNL SHL SDL NHL NDL HDL	16.5	16	.39
M 5	UL SL NL HL DL	28.52	26	.33
M 6	ASNHDL	139.9	31	.00

<u>Variables</u>	<u>Lambda</u>	Std.Val.
Segment Larceny Rate	.16	5.6
Neighborhood Nuisance	.11	3.4
Community Cohesion	08	-2.9
Community Disorganization	.084	2.9

Table 18: Log Linear Models of Home Larceny (L) Using Housing Structure Security (T), Segment Larceny Rate (S), Neighborhood Nuisance (N), Community Cohesion (H) and Community Disorganization (D):personal Interviews Only

	<u>Models</u>	<u>Chi-Sq</u>	DF	<u>P</u>
Ml	TSNHDL	0	0	0
M 2	TSNHL TSNDL TSHDL TNHDL SNHDL	1.38	2	>.5
МЗ	TSNL TSHL TSDL TNHL TNDL SNHL SNDL SHDL NHDL	10.7	10	.38
M4	TSL TNL THL TDL SNL SHL SDL NHL NDL HDL	13.9	16	>.5
M5	TL SL NL HL DL	27.1	26	.40
M6	A S N H D L	138.3	31	.00

<u>Variables</u>	Lambda	Std.Val.
Segment Larceny Rate	.16	5.4
Neighborhood Nuisance	.11	3.8
Community Cohesion	08	-2.8
Community Disorganization	n .085	2.8

Table 19: Models and Likelihood Ratio Chi-Sq for Age (A), Race (R), Sex (S) of Respondent, Composite Exposure (E) at Work and Proximity to Dense Pools of Offenders (P)

					Marc	ina	als			<u>Chi-Sq</u>	DF	P
Ml	ARSI	P AF	RSE	SREI	ASE	P	ARE	P		.34	2	>.5
M2	ARS	RSI EP S	RS EP	SE A	ASP A	SE	AR	P	REP	2.02	8	>.5
МЗ	AR SI	AS	ΑE	AP	RS F	RΕ	RP	SE		8.81	16	>.5
M4				P						26.16	26	.454
M5	A F	R S	E							58.2	27	.006
M6	A F	₹ S	P							65.6	27	.001
M7	R S	БЕ	P							33.18	27	.19
М8	S A	E	P							26.7	27	.46
M9	A E	P								28.6	28	.44
M10	E	P								35.6	29	.185

Effect Parameters and Standard Values of M9

<u>Variables</u>	<u>Effect</u> <u>Parameters</u>	<u>Std</u> Values
Proximity	.155	3.5
Exposure	.1378	3.13

AGE	1= <35
RACE	1=Black, Other
SEX	l=Male '
COMPOSITE	1=High Exposure
EXPOSITE	

(Exposure was measured by a simple additive scale of items used to measure attractiveness, mobility at work, and access to the public at work. The distribution of these summed scores was divided at the median to obtain the variable included in this analysis.)

PROXIMITY 1= Near dense pools of offenders

Table 20: Models and Likelihood Chi-Square Ratios for Age (A), Proximity (P), Exposure (C), Attractiveness (H) and Guardianship (M)

				<u>Ma</u>	rgina	als	<u>Chi-Sq</u>	<u>DF</u>	<u>P</u>
Ml	APCH	APC	M AP	нм А	СНМ	PCHM	1.62	4	>.5
M2	APC PCI	APH H PHI	APM M PCI	ACH M CM	ACM H	MHA	7.94	12	>.5
МЗ	APH	ACH	ACM	PCH	PHM	СМН	7.86	20	>.5
M4	APH	ACH	ACM	PHM	СМН		29.62	24	.197
M5	APH	ACH	PCH	PHM	СМН		105.79	24	.00
M6	APH	ACH	ACM	PCH	СМН		776.00	24	.00
M7	ACH	ACM	PCH	PHM	СМН		73.98	28	.0003

Effect Parameters and Standard Values of M3 for All Statistically Significant Main Effects and Interaction Effects of Independent Variables on Victimization at Work

	<u>Variables</u>	Effect Parameters V	<u>Std.</u> Zalues
Main Effe	cts		
	Age of Respondent	.063	2.13
	Proximity	.1527	5.15
	Exposure	.071	2.4
	Attractiveness	.1391	4.7
	Guardianship	.071	2.4
Two-way In	nteractions		
	Age X Exposure	055	1.84
Three-way	Interactions		
	Exposure X Attractiveness X Guardianship	.06	2.01

Table 21. Models, Likelihood Chi-Square Ratios, and Effect Parameters for Exposure (E), Guardianship (M), Attractiveness (T), Proximity (P), Age (A), Protective Measures (G) and Victimization of Employees at Work (V)

<u>Model</u>	CHI-SO	<u>DF</u>	<u>P</u>
M1 EMTPA EMTPG EMTAG EMPAG ETPAG MTPAG	2.95	2	.22
M2 EMTP EMTG EMTA EMPA EMPG EMAG ETPA ETPG ETAG EPAG MTPA MTPG MTAG MPAG IPAG	17.0	20	>.5
M3 EPMA EMGA ETMA ETMG PTMG PEMG	26.9	40	>.5
M4 PEMA EMGA ETMA ETMG PEMG	46.92	44	.35
M5 PAMA EMGA ETMG PEMG	96.0	52	.00

	<u>Variables</u>	Lambda	<pre>Std.Val.</pre>			
Main Effects						
Main Hilects	Proximity	.143	4.58			
	Attractiveness	.152	4.86			
	Guardianship	.08	2.57			
Two Variable Interactions						
	Exposure X Age	059	-1.89			
Three Variable Interactions						
Exposure X ship	Attractiveness X Guardian	.058	1.85			

Table 22: Log Linear Model Results Predicting Victimization At Leisure Using the Age (A), Race(R), and Sex(S) of Victims

	<u>Models</u>	<u>Chi-Sq</u>	<u>DF</u>	<u>P</u>
Ml	ARSV			
M2	ARV ASV RSV	5.23	1.0	.02
МЗ	AV SV RV	9.65	4.0	.04
M4	A R S V	100.9	7.0	.00

Significant Effect Parameters and Standard Values for the Best-Fit Model--M1

<u>Variables</u>	Lambda	Std. Val.
Age	.20	5.66
Race	.09	2.56
Three Variable Interactions		
Age X Race X Sex	08	-2.28

Table 23: Log Linear Model Predicting Victimization at Leisure (V) Using Exposure (E), Perceived Dangerousness (P), Age (A), Race (R) and Sex (S)

	<u>Models</u>	Chi-sq	DF	<u>P</u>
Ml	EPARV EPASV EPRSV EARSV PARSV	1.7	1	>.5
M2	EPAV EPRV EPSV EARV EASV ERSV PARV PASV PRSV ARSV	6.33	9	>.5
МЗ	EPAV ARSV	18.7	18	.41
M4	EPAV ARV ASV RSV	24.1	19	.19
M5	ARSV EPV EAV EPV	22.88	19	.24
M6	EPV EAV ERV ESV PAV PRV PSV ARV ASV RSV	22.7	17	.16
M7	EV PV AV RV SV	50.7	26	.00
M8	E P A R S V	299	63	.00

<u>Variables</u>	Lambda	Std. Valu
Exposure	.168	3.9
Perceived Dangerousness	.148	3.5
Age	.16	3.7
Race	.13	3.0
Two Way Interactions		
Age X Exposure	11	-2.62

Table 24: Log Linear Model Predicting Victimization at Leisure (V) Using Exposure (E), Proximity (P), Self-protection (G), Age (A), Race (R) and Sex (S).

			Mod	<u>els</u>				Chi-sq	<u>DF</u>	<u>P</u>
Ml		V EPGASV E RSV	PGRSV	EPA:	RSV :	EGARS	V	1.12	1	.29
M2	EPGA EGR GAR		GSV EI PGAR			EGAR' PGRSV	V	22.44	26	>.5
МЗ	EPGV EAR PAR ARS	V EASV E V PASV P	RSV 1	PSV 1 PGAV GARV	EGAV PGRV GASV	EGRV PGSV GRSV	J	20.31	29	>.5
M4	EPV PSV	EGV EAV GAV GRV	ERV GSV	ESV RSV	PGV	PAV	PRV	41.7	42	.48
M5	EAV	PRV ASV						135.6	55	.00
M6	EPV GAV	EGV EAV GRV GSV	ERV ARV	ESV ASV	PGV RSV	PAV	PSV	46.7	32	.32
M7	EPV	EGV EAV	PGV	ASV				63.9	53	.15
M8	EAV	EPV EGV	PRV	PSV	GAV	ARV	ASV	47	49	>.5
M9	EAV	EPV EGV	PGV	PRV	ASV			46	51	>.5
Mlo	EV	PV GV A	v RV	sv				75.27	57	.05
Mll	E P	G A R	s v					361.37	63	.00

<u>Variables</u>	<u>Chi-sq</u>	<u>DF</u> <u>P</u>
Exposure	.139	3.4
Self-Protection	.28	6.9
Age	.17	4.19
Race	.147	3.6
Two Way Interactions		

Age X Exposure

-.09 -2.2

Table 25: Log Linear Models Predicting the Use of Self-Protective Practices (P) Using Age (A), Race (R), Sex (S) of Respondent, Exposure (E), Central City Residence (C), and Victimization (V).

	<u>Models</u>	Chi-Sq	<u>DF</u>	<u>P</u>
Ml	ARSECP ARSEVP ARSCVP ARECVP ASECVP	.03	1	>.5
M2	ARSEP ARSCP ARSVP ASEVP ASCVP ASCEP AECVP RSCVP RSECP RSEVP RECVP SECVP	4.4	10	>.5
МЗ	ARSP ARCP AREP ASCP ASEP ASVP RSEP RSCP RSVP RCVP SECP SEVP SCVP ACEP AEVP ACVP RECP REVP	11.7	22	>.5
M4	ARP AEP ACP AVP ASP RSP REP RCP RVP SEP SCP SVP ECP EVP	34.5	42	>.5
M5	AP RP SP EP CP VP	127.28	57	.00
M6	A R S E C V P	908.66	63	.00

Significant Effect Parameters and Standard Scores for the Best Fit Model--M4

<u>Variables</u>	<u>Lambda</u>	<pre>Std.Val</pre>
Race	.1135	2.7
Exposure	.267	6.3
Central City Residence	.095	2.3
Victimization	.089	2.15
Two Variable Interact	tions	
Age X Central CITY	.066	5.78
Sex X Victimization	.058	4.08
Exposure X Central City	.061	2.07

Table 26: Log Linear Model Predicting Property Victimization at Leisure (V) Using Age (A), Race (R), Sex (S) of the Respondent, Exposure (E), and Perceived Dangerousness (D)

	<u>Models</u>	Chi-sq	<u>DF</u>	<u>P</u>
M1	ARSEDV	0	0	0
M2	ARSEV ARSDV AREDV ASEDV RSEDV	.89	2	>.5
М3	ARSV ARDV AREV ASEV ADEV RSEV RSDV SEDV	.38	8	>.5
M4	ARV ASV AEV ADV RSV REV RDV SEV SDV EDV	9.96	17	>.5
M5	AV RV SV EV DV	35.78	26	.09
M 6	EDV AEV REV RDV ARV	11.65	22	>.5

<u>Variables</u> <u>Std. Values</u>	Lambda	
Exposure or Time at Leisure	.25	5.19
Age of Respondent	.108	2.24
Race of Respondent	.116	2.39
Two Variable Interactions		
Exposure X Age	1102	2.32

Table 27:Log Linear Model Predicting Violent Crime at Leisure (V) Usin Age (A), Race (R), Sex (S), Perceived Dangerousness (D) and Exposure (E)

	<u>Models</u>	Chi-sq	DF	<u>P</u>
M1	ARSDEV	0	0	0
M2	ARSDV ARSEV ARDEV ASDEV RSDEV	.73	1	.39
МЗ	ARSV ARDV AREV ASDV ASEV ADEV RSDV RSEV SDEV	5.71	8	>.5
M4	ARV ASV ADV AEV RSV RDV REV SDV SEV	22.6	16	.12
M5	SDEV RSEV ARSV AREV ADV RDV	8.36	12	>.5
M 6	RSEV ARSV EDV AEV RDV SDV	12.34	15	>.5
M7	SDEV ARSV AEV ERV DRV ADV	15.77	15	>.32
M8	AV RV SV DV EV	40.82	26	.03

M9 A R S D E V Significant Affect Parameters and Standard Values for the Best Fit Model--M5

<u>Variables</u>	<u>Lambda</u>	Std. Values
Exposure or Time at Leisure	.149	2.18
Dangerousness of Areas in which Leisure Activities Pursued	.136	1.98
Age of Respondent	.24	3.51
Race of Respondent	.30	4.45
Two Variable Interaction	<u>ons</u>	
Age X Race	.158	2.3
Age X Race X Sex	146	-2.12

Table 28: Log Linear Models of Violent Victimization at Leisure (V) Using Age (A), Race (R), and Sex (S) of Respondents, Exposure (E), and Central City Residence (C)

	Models	<u>Chi-sq</u>	DF	<u>P</u>
Ml	All Five Variable Models	3.21	1	.07
M2	All Four Variable Models	11.08	8	.197
МЗ	All Three Variable Models	27.26	16	.034
M4	All Two Variable Models	51.45	26	.002
M5	Marginal Effects Model			

Significant Effect Parameters and Standard Values for the Best Fit Mod

<u>Variables</u>	<u>Lambda</u>	Std. Valu
Age	.24	3.87
Race	.239	3.85
Exposure or Frequenc Leisure Activity	y .1857	2.99
Central City Resider	.228	3.68
Two Variable Interactions	<u>.</u>	
Age X Race	.143	2.3
Race X Central City Resid	lence .136	2.2
Three Variable Interaction	ons.	
Age X Race X Sex	124	-2.00

Table 29: Significant Effect Parameters and Standard Values for Log Li Models of Personal Crime, Crime at Leisure, and Crime at Work.

<u>Variables</u>	Type of Crime		
Structural Variables	Personal	At Leisure	At Work
Age	.22 (8.8)	.11	.06 (2.1)
Race	n.s.	.12 (2.4)	n.s.
Sex	n.s.	n.s.	n.s.
Activity Variables			
Exposure	.17	.25	.071
Perceived Dangerousness		(5.2) n.s.	(2.4) .15
Mobility	n.a.	n.a.	(5.2) .07
Attractiveness	n.a.	n.a.	(2.4) .14 (4.7)