Chapter 5
Cross-Sectional Design and Linear Statistics in Vulnerability Research

In this chapter we examine the cross-sectional research designs and linear statistics used in community disaster vulnerability research. The foundation of vulnerability theory is based on cross-sectional data and linear statistics. Cross-sectional designs are by far the most popular type of research done on vulnerability. Similarly, linear statistics account for the vast majority of empirical results reported in the vulnerability literature. The advances in linear statistical modeling over the past several decades have made it possible to squeeze more value out of cross-sectional designs.

This chapter is structured with two main sections and a summary. We begin with an overview of cross-sectional design. A brief account of the characteristics distinguishing cross-sectional design is given, and the advantages of this design for vulnerability research are discussed. We compare cross-sectional designs to experimental designs and note some of the reasons for choosing a cross-sectional design over an experimental design. We also consider the utility of cross-sectional designs for both descriptions and hypothesis testing. Next we consider linear statistical models. We discuss and give examples of disaster vulnerability research using linear regression, logistic regression, hierarchical regression, path analysis, and latent variable structural equation modeling (SEM). We conclude this chapter with a summary of the linear methods used in developing vulnerability theory.

Cross-Sectional Design

Cross-stated designs are the most widely used type of research in the study of disaster vulnerability and resilience. The primary characteristic of cross-sectional design is data collected at one point of time; this is the basis for the name "cross-sectional design." Because the data are collected at one point in time none of the variables are manipulated. Similarly, all variables are assumed to vary naturally. Like other kinds of research designs, measures are taken on at least one variable and most often a set of independent variables and one or more dependent variables (de Vaus, 2001).

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The cross-sectional design is well suited for exploring or testing the relative importance of different variables. This design is also appropriate to describe clusters of interrelated variables. For example, considerable disaster vulnerability research has examined patterns of association among community socio-demographic variables. This research has found that race, gender, age, and socioeconomic status are associated with disaster vulnerability, susceptibility, resilience, wellness, and access to resources such as social capital (Bolin, 2007; Kaniasty & Norris, 2009; Norris, Stevens, Pfefferbaum, Wyche, & Pfefferbaum, 2008).

The cross-sectional design has a number of practical advantages. First, data can be collected more quickly because as noted above the data are collected at just one point in time. Most often this point in time has been after a disaster has occurred. There is no need to wait any amount of time for data collection, for example until an intervention has been performed. Second, with a cross-sectional design data can be analyzed shortly after data collection. Third, cross-sectional designs are typically less costly to execute than longitudinal or experimental designs. In a cross-sectional design there are no costs from applying an intervention, repeated sampling, or tracking respondents over several data collection points. Only a small percentage of vulnerability research studies use longitudinal designs (Norris, 2006; Norris & Elrod, 2006), and very few disaster vulnerability studies have used experimental designs (Galea & Maxwell, 2009).

When research with a cross-sectional design is cross-cultural or cross-national, the investigator must clearly specify the nature of the concepts in both cultures/societies. If such research is descriptive in nature, the variables can be measured with a high degree of specificity. Cross-cultural designs help to establish one dimension of generalizability among variables. Cross-cultural designs can accommodate the full range of variation characterizing variables, and higher degrees of variation allow for more precise parameter estimation. Finally, comparative cross-sectional designs allow for the development of new concepts, theoretical insights, and hypotheses.

Cross-Sectional Compared to Experimental Designs

In cross-sectional design independent and dependent variables need not be temporally contiguous, although in testing hypotheses careful attention must be paid to causal ordering. Careful thought must be given to causal ordering because the design provides no help in determining the direction of causal effects. It is impossible to include a control group in cross-sectional designs (Warwick & Lininger, 1975). On the other hand, observing the effects of race on life experiences can require a long time, making longitudinal and experimental designs less feasible than cross-sectional designs. In addition, certain attribute variables such as race, gender, and age cannot be manipulated by investigators.

Another difficulty with using experimental designs in vulnerability research is the impossibility of random assignment of individuals into racial, ethnic, or gender groups to form comparison or control groups. An added complication is that many independent variables of interest to investigators in vulnerability research, both attribute and relational, are associated together. For example, a person's age is positively associated with having disaster experience (Norris, Friedman, Watson, et al., 2002; Norris, Friedman, & Watson, 2002), and negatively associated with size of the individual's social support networks as well as access to tangible social support after a disaster (Kaniasty & Norris, 2009). These associations make experimental control of extraneous variables difficult if not impossible.

Certain analyses in conjunction with cross-sectional designs can loosely approximate the design advantages of experimental research. Cross-sectional designs which use elaboration can partially address the issue of group comparability through control of extraneous variables. The problem of temporal continuity can be addressed through theoretical specification of intervening variables. Even when experimental designs are used, it is difficult to establish causal relations because it is impossible to identify or control all extraneous variables (Blalock, 1964). Reality is messy, and our attempts to develop linear approximations to aspects of this reality are invariably to some degree incorrect. As Deming (1994) noted, "all models are wrong; some are useful."

Description and Hypothesis Testing

Cross-section designs can address both description and hypothesis testing. With designs for description the primary goal is precise measurement of a phenomenon using validated instruments. Description sometimes leads to the creation of hypotheses. Such hypotheses are often examined initially using the development sample even though this does not and cannot constitute a test of the hypothesis. Eventually and necessarily hypotheses must be tested with data from a new sample. Hypothesis testing goes beyond the empirical evidence of relationships among variables by explaining why or how it is that those relationships exist. Theory is expressed through hypotheses. Hypotheses state causal direction, relationship polarity, and a reason for the relationship. Often the logic underlying the reasons for the relationships reflects the theory.

Theory requires multiple independent studies carried out by different researchers. A researcher at a given point in time may initiate theoretical inquiry by stating and testing one or more hypotheses. Only when these initial findings and the reasons for them are upheld by other researchers we do have the beginning of theory. Theory is supported by replication through numerous independent research studies in a variety of contexts (Zakour & Gillespie, 2010). Theories persist by resisting refutation. That is, theory is considered valid as long as data continue to support its hypotheses. Since the data from any sample may be consistent with and support more than one hypothesis, it sometimes happens that the data support both the original hypothesis and a competing hypothesis. When this happens, it is necessary to refine the theory.

In cross-sectional designs, much can be learned about the nature of the relationship between any two variables by controlling for a third variable, traditionally called a test variable (Rosenberg, 1968). This kind of analysis yields convincing support for vulnerability theory. Theory and previous research is used to guide the selection of variables for inclusion. The theory implies a certain pattern of relationships among the variables.

Linear Statistics

In this section we describe a series of linear statistical models. Each of these models is part of the same statistical family, called the general linear model (McCullagh & Nelder, 1989). We begin with multiple regression and logistical regression, then progress through hierarchical regression, path analysis, and latent variable modeling. Except for logistical regression, which is an adjustment to accommodate categorical data, each step of this progression reveals an expansion in model capability, giving researchers increasing flexibility in testing hypotheses. While the more advanced statistical models allow testing of complex structures, the basic assumptions of the general linear model apply to all of these models.

An early and critical consideration for all statistical models is the selection of variables. Careful selection of variables is arguably the single-most important aspect in addressing any research question. There is no method that can correct or overcome the error and distortion introduced by choosing irrelevant or inappropriate variables or by omitting relevant and appropriate variables. It is the content of the variables that connects directly with the questions about disaster vulnerability. These questions reflect particular aspects of the theory. Each of the statistical models discussed has the capacity to answer a variety of research questions.

Regression

Linear regression describes the relations of a continuous dependent variable on a linear combination of independent variables. Regression is particularly useful in naturalistic settings with continuous variables that cannot be manipulated. Multiple regression coefficients indicate the amount of explained variance in a single dependent variable; the variance accounted for by the set of independent variables. Sequential regressions indicate how much of the variance in a dependent variable is accounted for by each independent variable, after the variance accounted for by the independent variables already entered into the regression equation are controlled for (Tabachnik & Fidell, 1996).

Regression can be used to predict within a limited time frame. Multiple regression coefficients are directional. For example, if we estimate the relationships between three variables in two alternative models—Model A, $x1 = a + b2 \times 2 + b3 \times 3 + e$, and Model B, $x2 = a + b1 \times 1 + b3 \times 3 + e$—we will find that the relationship between $x1$

and $x2$ will be different in the two models. Generally, the model selected as most accurate is the one most consistent with the theory. Although the directionality of multiple regression coefficients is suggestive, the fact that cross-sectional data is collected at a single point in time means that predictions cannot be established through the use of regression alone. Additional evidence supporting or failing to support prediction can be produced by dividing samples into subgroups where various levels of the dependent variable can be examined to more precisely specify the pattern of associations between each independent variable and the dependent variable.

Several recent studies have used regression analysis to find ways of facilitating the resilience and psychosocial functioning of persons with disabilities. Arlikatti, Lindell, Prater, and Zhang (2006) measured the lowest category of hurricane that respondents intended to evacuate for. This variable is a dispositional variable associated positively with actual behavior in a hurricane disaster. The authors included contextual variables such as warnings from public officials and from informal networks of family, friends, and neighbors. Though this study surveyed respondents at a single point in time, prediction of future behavior was possible through the use of a dispositional variable known to be positively associated with the future behavior of interest (Lindell, Lu, & Prater, 2005).

McGuire, Ford, and Okoro (2007) used 2003–2004 data from the Behavioral Risk Factor Surveillance System to estimate the number of individuals in the New Orleans Standard Metropolitan Statistical Area with a disability who needed assistive equipment during disaster evacuation. As Fig. 5.1 shows, evacuation before a hurricane is critical, given the large percentage of the city below sea level (shaded in blue). The focus of this research was not only to provide information for emergency planners regarding the need to evacuate disabled individuals with their equipment, but also to estimate the need for this equipment during evacuation by the categories of respondents. Their sample consisted of 47,840 individuals aged 65 and older with a disability. Of this number over half—24,938 (52%)—required the use of special assistive equipment. The investigators found that the need for assistive equipment was positively associated with being female, unmarried, and white, and negatively associated with self-reported health status (from poor to excellent). This finding is consistent with the sixth assumption of vulnerability theory that demographic variables are associated with vulnerability but do not cause vulnerability (Chap. 2, p. 12).

Logistic Regression

Logistic regression is similar to linear regression, except that logistic regression provides the probability of a case being in one condition versus another. Logistic regression is often used when the outcome variable is a health condition, such as the presence or absence of illness in a population. This means that the dependent variable in logistic regression is either dichotomous, nominal, or ordinal with only

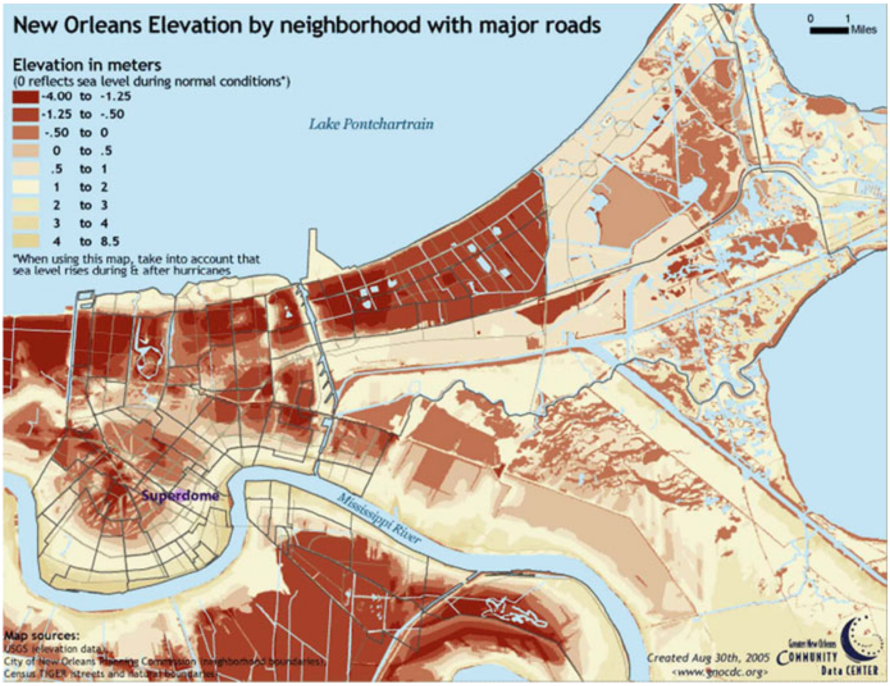

Fig. 5.1 Elevation of New Orleans, Louisiana. This figure shows the elevation of areas of New Orleans with elevations below sea level are in a darker shade. *Source*: http://www.flickr.com/photos/maitri/2232651989/sizes/o/in/photostream/

a few categories. Logistic regression is particularly useful when the relationship between the dependent variable and one or more of the predictor variables is assumed to be nonlinear. Like linear regression, logistic regression is useful because a linear combination of a set of two or more predictor variables can be measured as continuous, discrete, or dichotomous variables. Unlike linear regression, logistic regression makes no assumptions about predictor variables in terms of normal distribution or linear relationships among predictor variables.

The major goal of logistic regression is to predict the category of outcome on a probabilistic basis. For example, the two categories might be "resilience trajectory" and "progression to vulnerability." The investigator may wish to understand the probability of selected communities being assigned to the resilience versus the vulnerability conditions. The predictors could be the characteristics of resources useful for disaster response and recovery, such as robustness, redundancy, and rapidity of mobilization. Another potential set of predictors involves the nature of exposure to the hazard, including severity, duration, and the degree to which the disaster was a surprise.

The investigator may also want to understand which predictors, and interactions among predictors, are related to the probability of placing cases in the resilience category as compared to the vulnerability category. Because not all of the predictors or interactions among predictors will be related to the dependent variable, the investigator

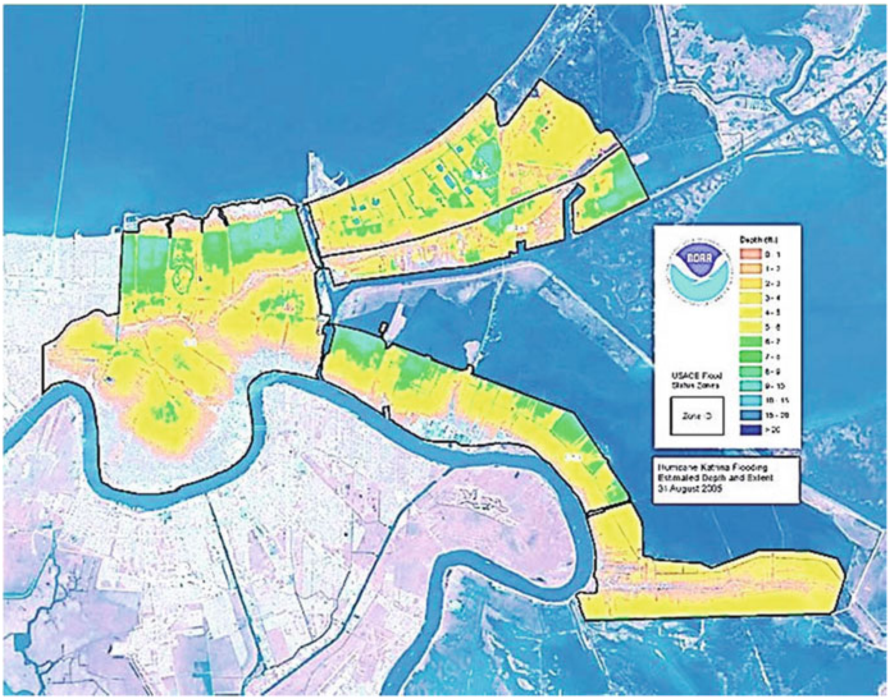

Fig. 5.2 Flooding in New Orleans after Hurricane Katrina. *Source*: http://www.katrina.noaa.gov/maps/images/katrina-flood-depth-estimation-08-31-2005b.jpg

can use goodness-of-fit tests to choose the logistic regression model which best predicts the outcome, with the fewest number of predictors. Logistic regression methods can also help in finding the relative importance of independent variables in predicting the outcome. Some two-way or higher order interactions among predictor variables may contribute to predicting the outcome of either resilience or vulnerability. For example, rapidity of resource mobilization may interact with the degree of unexpectedness of the hazard to increase the probability of either resilience or vulnerability.

Burnside, Miller, and Rivera (2007) examined the determinants of disaster evacuation in New Orleans several years before Katrina occurred. Figure 5.2 is a depiction of the depth of flooding in Hurricane Katrina, and the figure emphasizes the necessity for accurate hurricane and flood risk assessment by residents of New Orleans. Because there were two values for the dependent variable (1 = evacuate, 2 = shelter in place), logistic regression was used to analyze the data. One dispositional independent variable in this study was assessment of significant personal risk from major hurricanes. Data were collected over a 6-week period using random digit dialing to interview respondents by phone. There was a single wave of phone interviewing. Several demographic variables, a number of dummy variables which indicated whether respondents relied on different potential sources of information, and a risk assessment variable were all part of the interview schedule.

The risk assessment variable along with several of the information source dummy variables (reliance on governmental officials, television/internet, or family and relatives for evacuation warnings) were shown to add significantly to prediction of intention to evacuate in a category-3 hurricane. Because intention to evacuate is a dispositional variable shown to be strongly related to actual evacuation in a major hurricane, the cross-sectional design in this study showed support for the hypothesis that evacuation behavior is predicted and likely caused by the use of trusted sources of information.

Hierarchical Regression

Hierarchical linear models extend regression analysis. This technique goes beyond regression by testing the causal connections among exogenous, intervening, and outcome variables of interest. Methods for using regression analysis to understand the impact of variables at one level of analysis on variables at another level of analysis have been useful in vulnerability research on social capital and social networks (Zakour & Gillespie, 2010).

Hierarchical logistical regression methods use betas obtained at one level of analysis as error coefficients for regressions examining relationships among variables at another level of abstraction (Wellman & Frank, 2001). This technique is consistent with the idea that disasters are multidimensional and affect systems at all levels (Soliman, 1996; Zakour, 2008b). The network of an individual is often studied to understand which aspects of the network affect the amount of social support the individual receives. Hierarchical models assess the effects of others on social support at the first level, and the effects of the whole network on social support at the second level. We can also examine the interaction effects of variables at the different levels.

In their multilevel analysis of social support, Wellman and Frank (2001) were able to distinguish the effects of particular others from the network effects on social support in an emergency. Relationships among parents and adult children were shown to be more likely to involve social support in an emergency. Networks with a higher percentage of parents and adult children were also more likely to involve social support among parents and adult children. Relationships with people who were accessible were associated with provision of social support in an emergency. Additionally, networks with higher percentages of people who were accessible were more likely to involve the provision of social support in an emergency.

Networks of women were more likely to involve provision of social support in an emergency. At the network level, networks with a high percentage of women as actors were especially likely to involve provision of social support in an emergency. Finally, the effect of reciprocity on the provision of social support represents a different pattern of relationships than shown with parents and adult children. The reciprocity of individual ties does not add any unique and significant explanation of variance (Wellman & Frank, 2001). The authors suggest that exchange relationships and the frequency of exchange are important for building shared meaning within networks, and especially norms of reciprocity and social support in emergencies.

With contextual variables we can explore the conditions under which relationships among variables exists. For example, relative need in a disaster may determine the amount of social support and aid that the altruistic community provides to individuals, but this relationship might only hold in rural communities of developed nations, but not in urban communities or in rural communities in less-developed nations. When the original interpretation of the correlation among variables is challenged by seeking conditional relationships, the danger of excessively global or inexact generalizations is reduced. If interpretation of a relationship is radically revised through finding conditional relationships, this revision can press theory in new directions. Use of designs which can potentially reveal conditional relationships facilitate comparative research which includes several different kinds of communities in a single research project. Conditional relationships can provide new theoretical insights and hypotheses.

Path Models

Path analysis facilitates testing theoretical models. While regression models explain variance in a dependent variable by a linear combination of independent variables, path analysis goes beyond regression to determine indirect and direct relationships among a set of variables. Path models are developed to gain a more complete understanding of the relationships between all of the variables, regardless of whether they are independent, mediating, or dependent variables in a regression. The pattern of relationships in a theoretical model goes beyond the contribution of each independent variable to the dependent variable's variance, to more precisely describe the set of relationships (Zakour & Gillespie, 2010).

Path diagrams display a set of related variables with unidirectional arrows among the variables. By convention the unidirectional arrows are between two variables, with the arrows pointing to the right side of the diagram or sometimes upward or downward. The unidirectional arrows represent the direction of causality from one variable to another, so that the exogenous variable(s) is (are) on the left side of the path diagram. Most of the variables will have direct or indirect relationships to other variables on the right side of the diagram. When one variable has a single arrow pointing to a second variable, the first variable has a direct effect on the second variable.

Figure 5.3 shows the direct effects of rapidity of resource mobilization on the network of first responders and vulnerability. If one variable has an effect on a second variable, but only through a mediating variable, then this effect is indirect. Figure 5.3 shows the indirect effect of rapidity of resource mobilization on vulnerability through the network of first responders. It is possible for a variable with a direct effect on another variable to additionally have an indirect effect on this variable. Figure 5.3 shows both the direct and indirect effects of rapidity of resource mobili-

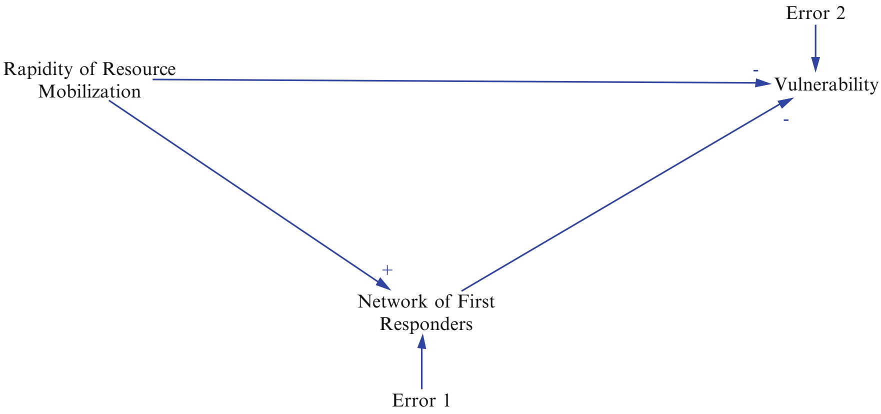

Fig. 5.3 Effects of rapidity of resource mobilization and network of first responders on vulnerability

zation on vulnerability. The direct and indirect effects of independent variables on other variables can be summed to reproduce the zero-order correlation matrix for the variables in the path model (Zakour & Gillespie, 2010).

Variables in path models are ordered causally, and the paths (represented by lines with one arrow) are unidirectional. A first step in path analysis is to determine the causal order for the variables that are to be included in the model. The process of ordering variables should be based on theory (Zakour & Gillespie, 2010). Not only must a causal chain of variables be postulated, but also branches may occur in the causal chain. Theory can describe which variables cause other variables, which variables are associated but have no causal relationship to each other, and which variables are outcomes of other variables. There are typically no feedback loops in path models. Most published path models are recursive, which means that the causal flow is entirely unidirectional.

An exogenous variable in a path model is the first variable in the causal chain and appears by convention on the left side of a path diagram. Exogenous variables are independent variables; the variance of exogenous variables is not explained by any other variable or set of variables. Because the variance of exogenous variables is unexplained by the model, it is desirable to have as few exogenous variables as possible, ideally just one. The exogenous variable is antecedent to other variables in the path model.

Endogenous variables are mediating and dependent variables. An endogenous variable is one that is explained by one or more variables in the path model. Some endogenous variables will be both independent and dependent variables in a causal chain. These variables are called intervening or mediating variables. Path models not grounded in theory are worthless (Freedman, 1992). Careful consideration of theory and empirically informed order of causality is essential to useful applications of path modeling.

There are at least five types of potential test factors which need to be considered in developing path models: (1) extraneous, (2) intervening, (3) antecedent, (4) suppressor, and (5) distorter variables (Rosenberg, 1968). It is important to understand which of these types of test variables is represented among the variables included in a study design. Extraneous, antecedent, and intervening variables are best understood through development of path models or structural equation models. Intervening variables in cross-sectional research can partially address the issue of lack of temporal contiguity among independent and dependent variables. Suppressor and distorter variables may reveal that the association between two variables is shown to be greater, less, or even reversed in valence when the test variable is controlled for (Zakour & Gillespie, 2010).

In determining causal sequences, some variables in a path model will be antecedent variables. Introduction of a variable as an antecedent variable is an effort to clarify influences which precede a relationship between independent and dependent variables. Some antecedent variables will have a direct effect on both independent and dependent variables. These antecedent variables are interpreted as being proximate causes in the relationship between independent and dependent variables. Proximate causes are direct causes of one variable on another. Other antecedent variables are among the first variables in a causal chain, and can be interpreted as distal or ultimate causes. Distal causes trigger a process that ultimately changes the value of an endogenous variable. To interpret any variable as an antecedent variable, the test variable and the independent and dependent variables must all be related to each other.

Several recent studies have used path models related to vulnerability research and social capital in disasters. Zakour (2008a) studied the effects of the social capital of disaster-relevant organizations in a southern metropolitan area. Information on disaster social service and emergency management organizations was collected using a mail survey questionnaire. The items in this mail survey included (a) the organizational level of capacity to provide evacuation services, (b) organizational location in the metropolitan area, and (c) cooperative links with other disaster-relevant organizations. Organizations that employed client-centered methods of service delivery and enjoyed higher levels of social capital had higher evacuation service capacities and larger geographic ranges in a disaster.

Latent Variable Structural Equation Models

SEM is a form of statistical analysis that examines causal relationships among variables more effectively than regression and path analysis. It is more effective because it estimates measurement error and removes this error from the estimates of theoretical parameters. There are two parts to an SEM model: the measurement parameters and the theoretical parameters. Figure 5.4 shows three measurement parameters for each of two latent variables and one theoretical parameter, namely the effect of rapidity of resource mobilization on vulnerability. Unlike traditional regression methods, in SEM there may be one or more dependent variables. Both independent and dependent variables may be either discrete or continuous.

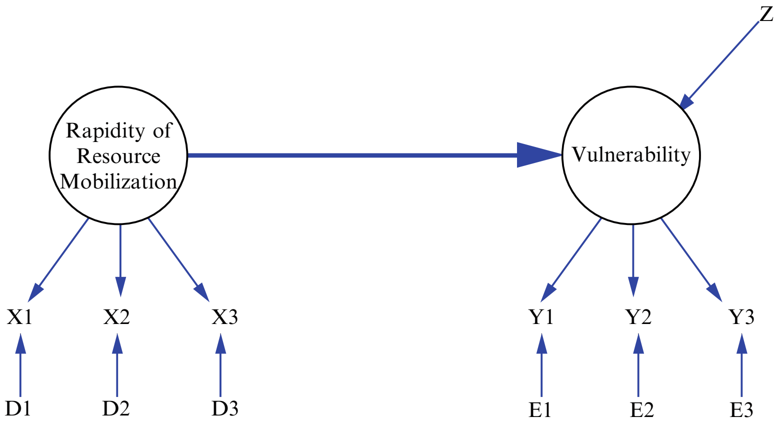

Fig. 5.4 Structure equation model of relationship between rapidity of resource mobilization and vulnerability

The variables in full SEM models are combinations of observed variables and latent factors (unobservable variables). SEM includes confirmatory factor analysis which estimates factors from sets of measured variables (Zakour & Gillespie, 2010). Figure 5.4 shows how rapidity of resource mobilization is implied by the pattern of associations among X1–X3, and vulnerability is implied by the pattern of associations among Y1–Y3. The arrow pointing toward a dependent variable and from an independent variable in the path model developed through SEM represents the direct or main effect on the dependent variable. Notice in Fig. 5.4 that the latent variables of rapidity of resource mobilization and vulnerability are direct causes of the observed variables X1–X3 and Y1–Y3; the variance not explained by the latent variables is represented in the error terms d1–d3 and e1–e3 for each of the observed variables. The main interest in Fig. 5.4 model would be the effect of rapidity of resource mobilization on vulnerability.

SEM with latent variables extends linear methods to enable more complex models of relationships among sets of independent and dependent variables. SEM is superior to the other linear techniques in this chapter (Ullman, 1996) because it encourages the use of multiple indicator concepts, establishes the reliability and validity of the variables used, extracts measurement error from theoretical parameters, assesses all parameters simultaneously, and easily handles reciprocal feedback relationships (Gillespie & Perron, 2007).

The ability to estimate latent variables simultaneously with the testing of theoretical parameters is a huge advancement for vulnerability and resilience research. Factor analysis reveals latent variables (factors), which can then be used either as independent or dependent variables in a structural equation model. Latent variables are inherently theoretical in the sense that they account for the pattern of correlations among a set of observed variables. Validity coefficients are now routinely reported in tests of confirmatory factor models as well as in fully specified

SEM models. Precise specification of unobservable constructs such as vulnerability, effectiveness, and many others is now possible.

The complexity of relationships can be further examined by elaborating these relationships with mediating variables. Mediating variables account for a part of or all of the variance shared between an independent and a dependent variable. In SEM, identification of a mediating variable means that either the independent variable has either only an indirect effect on the dependent variable, or that the independent variable has both a direct and indirect effect; this is called partial mediation. The use of mediating variables along with antecedent variables in SEM allows the investigator to more precisely trace out causal sequences. Theoretical reasoning and logic allow the investigator to determine if a variable is a mediating variable rather than an extraneous variable.

Rogge (1996) compared counties in eight southern states. Data from 330 counties in eight states were compared by census variables (e.g., population density) and by toxic risk. Data was at the county level only. All census data was from the 1990 U.S. Census and all data on toxic risk was from the EPA's 1992 Toxic Release Inventory. Toxic risk was operationalized as the pounds of fugitive emissions per square mile in each county. Though data was from 1990 and 1992, the 2 years do not represent a time series, because different variables came from 1990 versus 1992. An important result from this study was that population density was most strongly associated with toxic risk. More urban counties and their communities were found to be the most vulnerable to toxic emissions. This finding supports the second assumption of vulnerability theory regarding the uneven distribution of vulnerability (Chap. 2, p. 9).

Summary

Much has been learned about disaster vulnerability and resilience through cross-sectional research designs in combination with a wide range of linear statistical models. Multiple regression, logistic regression, hierarchical regression, path analysis, and SEM with latent variables each facilitate assessing particular kinds of questions. It is important to craft the research design for each kind of question and the circumstances prevailing at the time of the study (Gillespie & Streeter, 1994). The statistical methods discussed in this chapter cannot correct or adjust for a poor research design. However, appropriately selected and applied statistical methods complement the research design and facilitate increased precision. We anticipate the increasing use of SEM across the vulnerability and resilience fields.

Four of the studies discussed in this chapter produced results which support an assumption of vulnerability theory. Rogge's (1996) study of toxic emissions supports the second assumption of vulnerability theory that "Vulnerability is not evenly distributed among people or communities" (Chap. 2, p. 18). Urban counties with the highest population density were more vulnerable to toxic emissions than rural counties.

Further study is needed to find out the mechanisms by which population density increases vulnerability.

Burnside et al. (2007) provide support for the fourth assumption of vulnerability theory, which states that equitable distribution of resources decreases vulnerability (Chap. 2, p. 19). Reliance on trusted sources of information such as government, television, Internet, family, and relatives was positively associated with intention to evacuate in a category-3 hurricane. These communication sources provide information as a social resource relevant to making the decision to evacuate. The more widely available and evenly distributed these communication sources are, the less vulnerable is the community.

Research on functional needs of persons with a disability by McGuire et al. (2007) supports the sixth assumption of vulnerability theory, which asserts that "Social and demographic attributes of people are associated with but do not cause disaster vulnerability" (Chap. 2, p. 22). White females tend to live longer than other categories of people, and they are more likely to require assistive equipment in a disaster evacuation. Unmarried older women may have outlived their husbands and are less likely to have social support in coping with a disability. This appears to be an age effect since as noted above networks of women were more likely to involve provision of social support in an emergency.

The work of Wellman and Frank (2001) support the tenth assumption of vulnerability theory that "Culture, ideology, and shared meaning are of central importance in the progression to disaster vulnerability" (Chap. 2, pp. 24 and 25). Exchanges of social support within networks help to build shared meaning and norms of interaction among the actors. From their interaction in networks actors develop and are influenced by norms of support among adult children and their parents, and among non-related actors. Norms of social support in emergencies also develop in networks with higher percentages of accessible ties, women, and ties of reciprocity.

This chapter covered the characteristics of cross-sectional design and introduced the most frequently used statistical models in vulnerability research. In Chap. 6, we provide a more detailed account of the types of relationships in vulnerability theory, more in-depth information about the statistical models, and more findings from the research using these models. Chapter 6 is an extension of Chap. 5 and further acknowledgement of the critical role played by linear statistics in vulnerability theory.