NOTE ON RESEARCH METHODOLOGY

Introduction to multiple regression for categorical and limited dependent variables

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Multiple regression is a versatile and powerful statistical method that can be used to model simultaneously the effects of multiple independent variables on a dependent variable (for example, Cohen & Cohen, 1983; Fox, 1997; Pedhazur, 1997). The simultaneous examination of independent variables makes it possible to estimate their independent and combined effects; to determine more accurately the direction and strength of their effects; to rule out spurious effects; to better understand, predict, and explain a dependent variable; and to control the probability of Type I errors. In addition, with multiple regression it is possible to model main, interacting, or curvilinear effects and to examine the incremental improvement in a model brought about by the addition or deletion of independent variables. Furthermore, multiple regression can accommodate any combination of nominal, ordinal, or interval level independent variables. Finally, multiple regression is useful for the analysis of data collected using diverse research designs, including experimental, quasi-experimental, and nonexperimental designs.

Most social work researchers are familiar with the linear regression model, also sometimes referred to as ordinary least squares multiple regression, or simply multiple regression (Cnaan & Cascio, 1999; Gutierrez, Fredricksen, & Soifer, 1999; Harrington, 1999; Icard, Longres, & Spencer, 1999; Miller & MacIntosh, 1999; Nash & Bowen, 1999). Binary logistic regression also is used increasingly in social work research to model dichotomous dependent variables (see, for example, Drake, 1996; Rosenthal & Rosenthal, 1991; Smith, Sullivan, & Cohen, 1995; Zuravin & DePanfilis, 1997). These are only two of a large number of available multiple regression models (Fox, 1997; Greene, 2000; Long, 1997).

In addition to binary dependent variables, many dependent variables in social work research are multicategorical, ordinal, counted, censored, or assessed using truncated populations. Long (1997) referred to such variables as categorical and limited dependent variables (CLDVs). Most social work researchers are not aware of the numerous multiple regression models for analyzing CLDVs, the considerations involved in the selection of the most appropriate model, or the consequences of using linear regression to model many CLDVs. This lack of knowledge about multiple regression methods for CLDVs is unfortunate because many of the dependent variables of interest in social work are CLDVs that should not be modeled using linear or binary logistic regression.

Using a multiple regression model inappropriate for the characteristics of the dependent variable at hand can have a number of undesirable consequences (Breen, 1996; Greene, 2000; Long, 1997). Most notably, perhaps, the effects of independent variables might be over- or underestimated (that is, "biased"). In addition, parameter estimates might be "inefficient" (vary more from sample to sample) or "inconsistent" (have sampling distributions whose variability does not decrease with larger samples—Fox, 1997; Long, 1997; Marriott, 1990; Nunnally & Bernstein, 1994).

The purpose of this article is to extend the knowledge of alternative multiple regression models among social work researchers so that they will be in a better position to accurately model important dependent variables of interest to the profession. To this end this article

- defines and distinguishes among different types of CLDVs
- discusses the similarities and differences between linear and CLDV multiple regression models
- provides an overview of multiple regression models for CLDVs
- discusses key considerations involved in the selection of the most appropriate model from those available
- discusses briefly computer software available for estimating CLDV multiple regression models
- directs the reader to reference books in this area
- provides examples from the social work literature illustrating the use of each CLDV model discussed, where available.

Examples of published social work research illustrating the use of CLDV models were obtained in three ways. First, an electronic search of *Social Work Abstracts* (1977–March 1999) was conducted.

CCC Code: 1070-5309/01 $3.00 © 2001, National Association of Social Workers, Inc.

In conducting this electronic search, the following terms were used: logit, logistic, probit, multinomial, tobit, Poisson, negative binomial, binary, multicategorical, polytomous, ordinal, count, censored, censoring, truncated, truncation. Second, a search was made of the three social work journals we thought were most likely to publish research using these models: *Social Work Research, Social Service Review,* and the *Journal of Social Service Research.* These journals were searched for the years 1990 through September 1999. Third, we included selected examples from our recent research on the long-term correlates of family foster care where there were limited examples available from other sources (Buehler, Orme, Post, & Patterson, 2000). Thus, readers need to take into account that this search was limited to published studies involving the years, databases, and keywords enumerated.

In some of the social work research we reviewed, one CLDV model was used when another model might have been preferable. We discuss these cases to caution readers against inadvertently using these studies as examples of how to use particular models and to provide examples of issues and problems involved in model selection. Unless noted otherwise, to the best of our knowledge the remaining examples we review used the illustrated models appropriately.

CATEGORICAL AND LIMITED DEPENDENT VARIABLES

Categorical and limited dependent variables include dependent variables that are binary, multicategorical, ordinal, counted, censored, or from truncated populations (Long, 1997). Binary variables have two categories used to indicate that an event has occurred or that some characteristic is present (for example, placement in foster care coded as "yes" or "no"). Multicategorical variables have three or more unordered categories (for example, type of foster care placement coded as "kin care," "nonkin family care," "group home care," or "institutional care"). Ordinal variables have ranked categories with unknown distances between adjacent categories (for example, restrictiveness of foster care placement rated on a five-point ordered scale). Count variables indicate the number of characteristics or events during a given period (for example, number of foster care placements while in state custody).

Censored variables are those whose value is known over some range but unknown beyond a certain value because they only were recorded or collected (that is, censored) as being at or beyond that value (Greene, 2000; King, 1998; Long, 1997). For example, exact income might be recorded for those with income less than $100,000. However, for those with income greater than or equal to $100,000, exact income might be recorded as "greater than or equal to $100,000" rather than an exact amount. So, exact values for income are missing above $100,000, but the potential range of income is known. Typically censoring is used to elicit more reliable data or, as with income, to ensure confidentiality (King, 1998).

In the example given income is "censored from above." Censoring can occur from above ("right censored," sometimes referred to as a "ceiling effect"), below ("left censored," sometimes referred to as a "floor effect"), or both. Censoring can occur with continuous, ordinal, or count dependent variables (Nunnally & Bernstein, 1994). Some authors have referred to censored variables as "truncated variables" (Breen, 1996).

Censoring might not be apparent until after data are collected and an examination of the distribution of the dependent variable suggests an upper or lower value at which observations are clustered. For example, the frequency of enjoyable time spent by study participants with their children in the past 30 days might be measured using a six-point scale, ranging from never to almost every day, and results might indicate a large cluster of observations at the upper end of the scale. If such clustering is due to the way the data were collected or recorded, it is reasonable to treat the variable as censored. For example, the use of "almost every day" as the upper-scale anchor is analogous to using an upper-income category of greater than or equal to $100,000 because, conceivably, an upper category such as "every day" might have been used.

A distribution of a dependent variable with observations clustered at an upper or lower threshold does not in itself justify the treatment of a dependent variable as censored (Breen, 1996; Maddala, 1990). If such clustering is the result of decisions made by study participants, it is not reasonable to treat the dependent variable as censored. For example, if income spent on mental health services is clustered at zero, it does not necessarily indicate that income is censored but rather may indicate that numerous study participants decided not to spend any income on mental health services.

Truncated populations occur when cases are excluded from the population of interest on the basis of characteristics of the dependent variable (Greene, 2000). For example, Usher, Randolph, and Gogan (1999) noted that length of time in foster care sometimes is examined only for children who have been in care for some minimum amount of time, or placement changes sometimes are examined only for children who have some minimum number of placements. If the population of interest is all children in care, samples are selected from populations that are truncated by the amount of time in care in the first case and the number of placements in the second.

Whereas censoring is a characteristic of a variable, truncation is a characteristic of a population. Just as censoring can occur from above, below, or both, populations can be truncated from above ("right truncated") or below ("left truncated") or both. In the two examples the populations are truncated from below. Some authors have referred to truncated populations as "censored" populations (Achen, 1986).

Continuous variables have an infinite number of possible divisions between any two values (Cohen & Cohen, 1983; Nunnally & Bernstein, 1994). However, Cohen and Cohen (1983) and Nunnally and Bernstein (1994) noted that by this strict mathematical definition no empirically defined quantities would be considered continuous. Thus, Nunnally and Bernstein somewhat arbitrarily defined a variable as continuous if it can assume more than 11 ordered values. So, for example, a total scale score with 11 or more dichotomous items (or somewhat fewer items for multicategory items) would be considered a continuous variable. In contrast, individual Likert or other ordered-response scales with fewer than 11 ordered categories would be considered ordinal variables.

A continuous dependent variable is limited if it is censored or based on a truncated population. Linear regression is inappropriate when the dependent variable is censored or taken from a truncated population (Greene, 2000; Long, 1997). With few exceptions linear regression is appropriate only when the dependent variable is continuous, not censored, and not based on a truncated population.

SIMILARITIES BETWEEN LINEAR AND CLDV REGRESSION MODELS

A number of multiple regression models are available for CLDVs. However, those familiar with linear regression will find many important similarities between linear and CLDV models, and these facilitate the transition to CLDV models. Specifically, with linear and CLDV models:

- independent variables are combined as an additive function (for example, $\alpha + \beta_1 x_1 + \ldots + \beta_k x_k$)
- unstandardized and standardized slopes can be computed for each independent variable
- each independent variable parameter estimate has an accompanying test of statistical significance
- regression slopes indicate the independent variables independent contribution to the explanation or prediction of the dependent variable
- the sign of a slope indicates the direction of the relationship
- independent variables can be any level of measurement
- the same methods are used for coding categorical independent variables (for example, dummy coding, effect coding)
- independent variables can be entered hierarchically or using other methods (for example, backward selection)
- product terms are used to test interactions
- powered terms (for example, the square or cube or an independent variable) are used to test curvilinearity
- overall model fit can be tested, as can the incremental improvement in a model brought about by the addition or deletion of independent variables (nested models)
- residuals and outliers are used to diagnose model problems
- multicollinearity can present problems in estimation and interpretation.

DIFFERENCES BETWEEN LINEAR AND CLDV REGRESSION MODELS

Although there are many similarities between linear and CLDV regression models, there also are important differences. The most fundamental is that most CLDV models are nonlinear. In linear regression B_k (the effect of a unit increase in an independent variable) does not depend on the level of X_k or the level of the other independent variables in the model. In CLDV models B_k depends on both the level of X_k and the level of the other independent variables in the model. Thus, the interpretation of individual regression coefficients is more complicated for CLDV models. For example, for an adolescent girl the birth of each additional child might have a diminishing (that is, nonlinear) negative effect on the probability of completing high school, as indicated by probabilities of .25, .10, and .05 for the first, second, and third child, respectively (that is, unit increases in the independent variable), and these probabilities might be different for white and African American adolescents.

Linear and CLDV regression models rely on different methods for estimating parameters. Linear regression typically relies on ordinary least squares (OLS) estimation, whereas CLDV models for the most part rely on maximum likelihood (ML) estimation. One important implication of this difference is that CLDV models might require larger sample sizes (Breen, 1996; Long, 1997). The small sample properties of the ML estimators for CLDV models are largely unknown, and some data (for example, highly collinear independent variables, dependent variables with little variation) and models (for example, regression models for ordinal dependent variables) might require larger samples than others (Long, 1997).

Another important implication of the use of ML estimation is that the statistics used to test hypotheses and to quantify overall model fit are different from those based on OLS estimation. The t statistic is used to test hypotheses about individual parameters with linear regression, whereas the z or Wald statistic typically is used with CLDV models. The F and F-change statistics are used to test hypotheses about blocks of variables with linear regression, whereas the Wald, likelihood ratio, or Lagrange multiplier tests, and the difference X^2 based on the likelihood ratio X^2 are used with CLDV models. Finally, with linear regression R^2 and R^2-change are used to quantify the amount of variance in a dependent variable accounted for by a set of independent variables, and the amount of change in variance accounted for by the addition of independent variables, respectively. Statistics analogous to R^2 and R^2-change are available for some CLDV models, but considerable debate exists concerning their merit (Long, 1997).

CLDV REGRESSION MODELS

Six categories of multiple regression models for CLDVs, and selected variations within each model, are reviewed: (1) binary probit and logit models, (2) ordered probit and logit models, (3) multinomial probit and logit models, (4) Poisson and negative binomial models, (5) tobit model, and (6) truncated regression model.

Binary Logit and Probit Models

Binary logit and probit regression are both appropriate for modeling binary dependent variables (DeMaris, 1992; Hosmer & Lemeshow, 2000; Menard, 1995; Morrow-Howell & Proctor, 1993; Pedhazur, 1997). However, the choice between these two models is largely one of convenience and discipline-specific convention, because the substantive results are generally indistinguishable (Aldrich & Nelson, 1984; Greene, 2000; Long, 1997).

Binary logit regression (also known as logistic regression) has been used widely in the social work literature, whereas binary probit regression has not. The binary dependent variables modeled using logit regression in social work research include, but are not limited to, child maltreatment (Camasso & Jagannathan, 1995), receipt of child support (Caputo, 1996), service provision (Drake, 1996), child abuse investigation outcome (Smith et al., 1995), and foster care placement (Zuravin & DePanfilis, 1997). In addition, Rosenthal and Rosenthal (1991) provided a good example of the use of binary logit regression in their study of the effects of placement options on recidivism of juvenile offenders. The dependent variable was recidivism, coded "1" if a repeat offense was committed and "0" if a repeat offense was not committed. Both quantitative and categorical independent variables were used, and these included age, number of prior offenses, number of prior placements, number of follow-up months, type of care, type of offense, gender, and minority status. One interaction term also was included and tested.

Probit regression has been used to model a number of binary variables, including economic assistance received from families (Jayakody, 1998), adolescent cigarette use (Yarnold, 1999), returns home from and re-entry to out-of-home care (Courtney, Piliavin, & Wright, 1997), recidivism (Rosenthal & Rosenthal, 1991), payment of child support (Brown, 1995), fathers' visitation with children (Brown, 1995), choice of political candidate (Wattier, Daynes, & Tatalovich, 1997), whether a dental visit was made (Wiley, 1985), and participation in legal gambling (Albers & Hubl, 1997). In addition, Klawitter's (1994) research on child support awards provided a good example of the use of binary probit regression. The dependent variable was type of child support award, coded as "1" for a fixed-percentage award and "0" for a fixed-dollar award. Both quantitative and categorical independent variables were used, and these included father's prior earnings, father's age, mother's income, father's self-employment, father's unemployment, county's use of routine withholding, number of children, and year of final divorce judgment. Interaction terms also were included and tested.

Multinomial Probit and Logit Models

Multinomial probit and logit regression (also known as a polytomous logit or logistic regression) are appropriate for modeling multicategorical dependent variables (DeMaris, 1992; Fox, 1997; Greene, 2000; Hosmer & Lemeshow, 2000; Menard, 1995; Unrau & Coleman, 1998). The multinomial probit and logit models are extensions of binary probit and logit models, respectively, and with a binary dependent variable, the multinomial models reduce to their binary counterparts (Greene, 2000; Long, 1997). As with binary probit and logit models, the choice between the ordered probit and logit models is largely one of convenience and discipline-specific convention, given that the substantive results are generally indistinguishable.

The multinomial probit model has not been used in the social work literature. The multinomial logit model has been used in the social work literature only to a limited extent, despite the large number of multicategorical dependent variables of interest to social workers (for example, type of services needed, provided, or refused; maltreatment; vocational training; psychosocial problem; living arrangements; reasons for entry into care; maltreatment case disposition). It has been used to model discharge status (Courtney & Barth, 1996; Courtney & Needel, 1997), preferred types of out-of-home placement (Courtney, 1998), actual types of out-of-home placement (Barth, 1997), children's postdivorce living arrangements (Ganong, Coleman, & Mistina, 1995), types of dwelling currently occupied (Buehler et al., 2000), type of residence (Miller, 1994), type of dental services received (Wiley, 1985), service outcomes (Unrau & Coleman, 1998), family structure and welfare use choices of divorced or separated women (Hoffman & Duncan, 1988), and senior center attendance categorized as frequently, sometimes, or rarely. Miner, Logan, and Spitze (1993) noted that "the relation of the categories to one another is unclear" (p. 653) and so the categories were considered unordered.

In addition, research conducted by Unrau (1997) on services use after intensive family preservation provides a good example of the use of multinomial logistic regression. Type of services use was the dependent variable, and it was measured using three categories: (1) no service, (2) service without placement of the at-risk child in out-of-home care, and (3) service with placement of the at-risk child in out-of-home care. Both quantitative and categorical independent variables were used, and these included number of behavioral referral problems, service minutes per day, emotional referral problems, domestic problems, previous placement experience, and child physical abuse perpetrated by the parent.

Ordered Probit and Logit Models

Both ordered probit and logit regression are appropriate for modeling ordinal dependent variables, and they can be estimated with dependent variables that are censored from above or below (Clogg & Shihadeh, 1994; DeMaris, 1992; Fox, 1997; Greene, 1995, 2000; Long, 1997; McKelvey & Zavoina, 1975; Menard, 1995; Miller, 1991; Winship & Mare, 1984). These models also are known as ordinal probit and logit models, ordered polytomous models, proportional odds models, parallel regression models, and grouped continuous models (Long, 1997).

The ordered probit and logit models are extensions of binary probit and logit models, respectively (Greene, 2000). As with binary probit and logit models, the choice between the ordered probit and logit models is largely one of convenience and discipline-specific convention, given that the substantive results are generally indistinguishable (Long, 1997).

Although ordered logit and probit models are appropriate for modeling a number of dependent variables of interest to social workers (for example, any of a number of dependent variables measured using individual Likert or other ordered-response scales with a limited number of ordered categories), they have been used in the social work literature only to a limited extent. Ordered logit regression has been used to model health status (Piliavin, Westerfelt, Wong, & Afflerbach, 1994), severity of reoffense (Winamaki, 1997), smoking history (Murray, Istvan, Voelker, Rigdon, & Wallace, 1995), marital happiness (Buehler et al., 2000), fathers' responsibility to children (Brown, 1995), and severity of child abuse injury (Paddock, 1995). In addition, research by Nugent and Paddock (1995) provided a good example of the use of ordered logit regression. Severity of reoffense by juvenile offenders was the dependent variable, and it was measured using a single-item, four-point ordinal scale that ranged from no reoffense to reoffense in which the victim was harmed. Both quantitative and categorical independent variables were used, and these included youths' age, grade, race, gender, number of prior offenses, and number of siblings, in addition to stepfamily status, single-parent status, and victim–offender mediation treatment. Interaction terms and one squared term also were included to test for interaction and curvilinear effects, respectively.

Ordered probit regression has been used to model the severity of child abuse injury (Zuravin, Orme, & Hegar, 1994) and disposition of child physical abuse reports (Zuravin, Orme, & Hegar, 1995). In addition, research by Meyers (1995) on parents' dissatisfaction with the quality of child care provided a good example of the use of ordered probit regression. Dissatisfaction with child care quality was the dependent variable, and it was measured using a six-point scale that ranged from best possible to needs improvement. Both quantitative and categorical independent variables were used, and these included size of social network, mother's education, number of children under age 13, use of a child care center, use of family child care, a child age zero to two, a child age three to five, use of a voluntary referral service, and knowledge of available subsidies.

Finally, Queralt and Witte (1998) categorized the number of licensed child care center capacities into four ordered categories and modeled this variable using ordered probit regression. However, it would have been better to model the number of licensed child care center capacities directly using one of the models for count variables described in the next section.

There are two notable situations in which the ordered probit or logit models should not be used. First, they should not be used if the order of the categories of the dependent variable is ambiguous (for example, type of exit from foster care ordered as reunification, adoption, or independent living). Second, they should not be used if the "parallel regression assumption" is not met. This assumption has to do with the assumption that the slopes across the various comparisons among the ordered categories are parallel. This assumption is not easily tested and because it is important, creates some difficulties when using this model (a more detailed discussion of this assumption is beyond the scope of this article; see Long, 1997). In cases in which there is suspicion that this assumption might not be accurate, the data also could be analyzed using the multinomial probit or logit models discussed earlier. If the results are similar, then the results from ordered probit or logit models can be interpreted.

Negative Binomial and Poisson Models

Poisson or negative binomial models are appropriate for modeling count dependent variables, although the negative binomial model typically is more suitable (Gardner, Mulvey, & Shaw, 1995; Greene, 2000; Long, 1997). The reason the negative binomial model typically is more suitable is that the Poisson model assumes that the conditional variance equals the conditional mean, a situation known as "equidispersion." The Poisson model rarely fits in practice because in most cases the conditional variance is greater than the conditional mean, a situation known as "overdispersion." Overdispersion can occur if the occurrence of an event positively influences the occurrence of later events, a situation that sometimes is referred to as "contagion" (for example, a disrupted foster care placement might increase the probability of later disruptions; King, 1998; Long, 1997). The presence of overdispersion might not be known prior to data collection, and so it is important to test for overdispersion if the Poisson model is used; several methods are available for doing this (Greene, 2000; Long, 1997). The negative binomial model is an extension of the Poisson model that allows for overdispersion.

Negative binomial models, and at times Poisson models, are appropriate for a number of dependent variables of interest to social workers (for example, number of services needed, provided, or refused; school days missed; psychiatric symptoms; prenatal visits to a physician; placement changes; violent behaviors; children birthed or fathered; days in the hospital; client referrals; physician visits; behavior problems; criminal offenses; article citations; sexual partners; stressful life events; residence changes; placement rejections; spells on AFDC). However, these models have seen almost no use in the social work literature. Clearly both models warrant greater consideration in social work research.

Research by Tucker and Hurl (1992) on environmental factors and the use of family foster care provides a good example of the use of the Poisson model, but it is the only such example found in our review. The dependent variable was the number of foster homes approved for use during a specified 22-year period in the given area of study. Both quantitative and categorical independent variables were used, and these included indicators of the average age of children coming into care, the demand for care, legislative change, economic incentives, and the density of placements in the area. Squared terms also were entered to test for potential curvilinear effects.

Research by Croft (1999) on the stability of placements among foster children provided a good example of the use of the negative binomial model, but it is the only such example found in our review. A wide range of both quantitative and categorical independent variables were used, and examples of these included children's age, emotional and behavioral problems, physical disabilities, developmental disabilities, health conditions, reason for entry into care, placement restrictiveness, placement type, length of time in care, and numerous demographic characteristics. Interaction terms also were included and tested.

There is a variation of the negative binomial and Poisson models known as a "zero-inflated" model. A zero-inflated model is appropriate when there is a mix of two processes in the count variable, one that generates only zero counts, and another that generates both zero and positive counts. For example, consider parental visitation with children in foster care. Some parents might not visit because they lack transportation (a process that generates only zero counts), and some parents might be more or less willing to visit (a process that generates zero and positive counts). As another example, Buehler et al. (2000) modeled the number of children birthed or fathered using a zero-inflated negative binomial model. This model was used because some men or women might be unable to have children (a process that generates only zero counts), and others might vary in their willingness to have children (a process that generates zero and positive counts). In any case, the presence of such a process might or might not be known before data collection, and it is possible to test for this after data collection (Greene, 2000). As always, though, such post hoc tests should be used and interpreted with caution.

In addition to zero-inflated models, it also is possible to estimate Poisson and negative binomial models in which the dependent variable is censored from above or below (Greene, 1995). For example, in measuring the number of contacts between foster children and biological parents in the preceding month, data might be recorded as 0, 1, 2, or 3 or more, and so the number of visits in the previous months is censored from above. Or, study participants might be asked to list up to five people who provided social support, and so the number of those who provided social support is censored from above.

It also is possible to estimate Poisson and negative binomial models in which the population is truncated from above or below (Greene, 1995; Long, 1997). For example, if agency records are used to model the number of times families are reported to a social services agency for child abuse, a family must be reported at least once before entering the population, and so the population is truncated from below at zero.

Finally, as Gardner et al. (1995) noted, when modeling counts often it is necessary to control for the opportunity for the event to occur. For example, in modeling the number of out-of-home placements for foster children, it would be important to include length of time in state custody as a control variable in the regression model (Croft, 1999).

Tobit Model

The tobit model is appropriate when the dependent variable is continuous, but censored (Breen, 1996; Greene, 2000; Long, 1997). This model also is known as a censored regression model, because like linear regression it is appropriate for use with a continuous dependent variable, but unlike linear regression it is appropriate when the dependent variable is censored. Tobit models can be estimated with censoring from above, below, or both (Greene, 1995). For example, in measuring the number of hours worked weekly, an upper category of greater than or equal to 40 hours might be used, and so the number of hours worked is censored from above.

The tobit model has seen some use in the social work literature. It has been used to model the percentage of time spent living below the poverty line (Vartanian, 1999), degree of social and financial involvement by unwed fathers with their children (Brown, 1995), and the time to out-of-home placement among children in families that received intensive family preservation services (Fraser, Jenson, Kiefer, & Popuang, 1994). In addition, research by Bartfeld and Meyer (1994) on factors predicting child support compliance provided a good example of the tobit regression model. The dependent variable was the percentage of child support owed that was paid. The data were censored from above because overpayments were coded as "1." Predictors used in the model included father's income, support order as percentage of income, use of immediate withholding, year of award, mother's income, father's age, father's marital status, and child's age.

Three additional studies used tobit regression to model count variables, which seemingly would have been modeled better using one of the models for count variables discussed earlier. Specifically, Cohen, Tell, and Wallack (1988) modeled the number of nursing home entries and the total days per year spent in a nursing home, Monahan, Greene, and Coleman (1992) modeled the number of support group sessions attended, and Brown (1995) modeled the number of days in the past year fathers visited their children.

Maddala (1990) and others (for example, Breen, 1996) have argued that tobit regression often has been used inappropriately. Specifically, these authors have argued that tobit regression has been applied inappropriately to variables based solely on the fact that an observed distribution had a large proportion of values clustered at zero or some other limit. Such clustering might be the result of individuals' choices, in which case sample selection models might be more appropriate (Breen, 1996; Greene, 2000; Maddala, 1990). Or such clustering might be the result of censoring, in which case tobit regression would be appropriate. As Breen (1996) noted, the decision is a question of interpretation and theoretical plausibility, not a question of methodology.

Several studies reported in the social work literature appear to have used tobit regression because a large number of values were clustered at zero, although this clustering does not appear to be the result of censoring. These include the use of tobit regression to model the amount of court-ordered child support awards and payments (used because a large proportion of subjects received no awards or made no payments; Danziger & Nichols-Casebolt, 1990), amount of financial assistance received from families (used because a large proportion of subjects did not receive any financial assistance; Jayakody, 1998), amount of skilled and unskilled home care and institutional care used by elderly people (used because a large proportion of people used no services; Hernandez-Gallegos, 1992), dollar amount of authorized long-term-care services (apparently used because a large proportion of subjects had no authorized services; Karon, 1991), and amount of child support paid by fathers in the past year (used because a large proportion of fathers paid no child support; Brown, 1995).

The distinction between clustering that resulted from individuals' choices or to censoring was made by Maddala (1990) in the context of tobit regression, but it also applies to other models in which variables can be specified as censored and modeled as such. These include ordered probit and logit models and Poisson and negative binomial models.

Time to the occurrence of an event is a particular type of continuous variable that often is censored. This type of variable has received considerable attention in the social work literature (see, for example, Cheng, 1995; DePanfilis & Zuravin, 1999; Fraser et al., 1994; McMurtry & Lie, 1992; Patterson & Lee, 1998; Slonim-Nevo & Clark, 1989; Taylor, 1999). For example, time to exit from AFDC, psychiatric rehospitalization, or return home from foster care might be measured only for a circumscribed time during which some study participants do not experience the event of interest, and so time is censored from above. Although tobit regression has been used with such data (for a good comparison of tobit regression with other methods, see Fraser et al., 1994), in general, other methods known broadly as survival, event history, or duration models are preferable (for example, Hosmer & Lemeshow, 1999; Lee, 1992; Yamaguchi, 1991). A discussion of these methods is beyond the scope of this article.

Truncated Model

The truncated regression model is appropriate when the dependent variable is continuous and the population is truncated (Breen, 1996; Greene, 2000; Long, 1997). (As noted earlier, it also is possible to estimate Poisson and negative binomial models for count dependent variables from truncated populations.) To our knowledge this model has not been used in the social work literature. Models with truncation from above, below, or both can be estimated (Greene, 1995).

Although this model has not been used in the social work literature, it is not hard to think of examples where it should be considered: Usher et al. (1999) noted, length of time in foster care sometimes is examined only for children who have been in care for some minimum amount of time, or placement patterns sometimes are examined only for children who have some minimum number of placements. Such populations exclude children in care for less time or children with fewer placements, respectively. Or determinants of behavioral and emotional problems might be examined only for children in treatment foster care. Such populations exclude children with fewer behavioral and emotional problems because children are placed in treatment foster care because of such problems. Finally, the correlates of depression might be examined among clinical populations seeking treatment for depression. Such populations exclude those who are less depressed.

COMPUTER SOFTWARE FOR ESTIMATING CLDV MULTIPLE REGRESSION MODELS

There are three notable computer programs that can be used to estimate virtually all of the models discussed in this article. One is LIMDEP, a program designed by Greene (1995) for estimating CLDV and many other models. Information about LIMDEP can be obtained from www.limdep.com. Also, a student version of this program, along with documentation, can be downloaded free from www.stern.nyu.edu/~wgreene/Text/econometricanalysis.htm (this student version along with data sets also are included with Greene, 2000). Another program is Markov, a program designed by Long (1993). Information about Markov can be obtained from www.aptech.com/markov.html. The final program is Stata, and information about it can be obtained from www.stata.com.

SPSS and SAS, two general statistical programs familiar to most social work researchers, also can be used to estimate some of the models discussed in this article. SPSS (Version 10.0) can be used to estimate binary probit and logit models, multinomial logit models, and ordered probit and logit models. SAS (Version 7.0) can be used to estimate most of the models discussed in this article, including binary and ordered probit and logit models, multinomial logit models, tobit models, and Poisson and negative binomial models.

REFERENCE BOOKS

Long (1997) provided a comprehensive treatment of the CLDV models discussed in this article, emphasizing social science applications and providing a good starting point for social work researchers interested in these models. One of many especially useful features of the book is the clear and detailed discussion about the interpretation of the regression coefficients for each model, an especially difficult aspect of these models. Finally, Long also has a Web site that contains data sets discussed in his book and a syllabus for a course covering this material (www.indiana.edu/~jsl650).

Greene (2000) and others (for example, Maddala, 1983) have provided comprehensive but more advanced treatments of CLDV and other models in the context of econometrics. King (1998) has provided details about most of these models within the context of political science.

In addition to the books just mentioned, there also are a number of useful books that focus on a more limited range of models. A number of books are available that discuss the binary probit and logit models (Agresti, 1990; Aldrich & Nelson, 1984; DeMaris, 1992; Fox, 1997; Hosmer & Lemeshow, 2000; Menard, 1995). Several books are available that discuss the multinomial logit model (Agresti, 1990; Aldrich & Nelson, 1984; DeMaris, 1992; Fox, 1997; Hosmer & Lemeshow, 2000; Menard, 1995) and ordinal probit and logit models (Agresti, 1990; Clogg & Shihadeh, 1994; DeMaris, 1992; Fox, 1997; Menard, 1995). Finally, Breen (1996) has provided a good discussion of censoring and truncation, a detailed discussion of tobit and truncated regression models, and some discussion of other CLDV models.

CONCLUSION

Multiple regression is a versatile and powerful statistical method. However, given that many dependent variables of interest to social work researchers are binary, multicategorical, ordinal, counted, censored, or assessed using truncated populations, social work researchers need to broaden their understanding and use of multiple regression beyond linear and binary logit regression. Except for binary logit regression, multiple regression models for CLDVs have been underused in social work research. In particular, count models have been underused. Also, tobit regression sometimes has been misapplied in the studies in which it has been used.

If the dependent variable is continuous, not censored, and not from a truncated population, linear regression should be considered. If the dependent variable is binary, multicategorical, ordinal, censored, or from a truncated population, a CLDV model should be considered. More specifically, if the dependent variable is

- a binary variable, binary probit or logit regression should be considered
- a multicategorical variable, multinomial probit or logit regression should be considered

- an ordinal variable, the categories are ordered unambiguously, and the parallel regression assumption is met, ordered probit or logit regression should be considered (both can be estimated with or without censoring)
- a count variable, Poisson (given equidispersion) or negative binomial (given overdispersion) regression should be considered (both can be estimated with or without censoring, truncation, or zero inflation)
- a continuous censored variable, tobit regression should be considered
- a continuous variable assessed in a truncated population, truncated regression should be considered.

As with linear regression, the appropriate use of multiple regression models for CLDVs requires certain assumptions. Different models require somewhat different assumptions; violations of different assumptions in different models have somewhat different consequences; and methods for testing assumptions vary to some extent across models (Breen, 1996; Greene, 2000; Long, 1997). These issues are beyond the scope of this article. However, as with all statistical models, these are important issues that require careful consideration. Thus, in the description of model selection, we say that a certain model "should be considered" instead of saying more definitively that it "should be used." The assumptions underlying a specific model should be considered carefully before the model is used and the results interpreted.

Although this article provides an overview of major multiple regression models for CLDVs, there are a number of models for CLDVs not discussed here. For example, the *t* test and ANOVA can be treated as special cases of multiple regression (Cohen & Cohen, 1983; Pedhazur, 1997), and so CLDV models also can be applied to these simpler cases when the dependent variable is categorical or limited (for example, Buehler et al., 2000). Also, bivariate correlation models are available for continuous and ordinal variables that are censored from above, below, or both (Byrne, 1998; Jöreskog & Sörbom, 1993). It also is possible to estimate structural equation models with continuous and ordinal variables that are censored from above, below, or both (Byrne; Jöreskog & Sörbom). Under some circumstances discriminant (Dattalo, 1994; Pedhazur, 1997) and loglinear (Agresti, 1990; Combs-Orme, 1992) analyses can be used to model binary and multicategorical dependent variables. Finally, hierarchical linear models are available to model binary (Gibbons & Hedeker, 1994; Longford, 1993; Raudenbush, Bryk, Cheong, & Congdon, 2000), multicategorical (Raudenbush et al.), ordinal (Gibbons & Hedeker; Longford, 1993; Raudenbush et al., 2000), and count dependent variables (Longford; Raudenbush et al.). These are just a few such examples.

There also are a number of extensions of the models that are discussed in this article. For example, several of the models have been extended to handle violations of assumptions underlying the original model (for example, nonparametric models and parametric models that do not require certain assumptions such as homoscedasticity and normality) (for example, Greene, 2000; Long, 1997). As another example, the multinomial logit model has been extended to the case of nested choice sets (for example, a separated or divorced woman might decide to remarry or not and if not, to receive AFDC or not); this model is known as a nested logit model (Greene, 2000; Hoffman & Duncan, 1988). Again, these are just a few such examples.

There is a wealth of multiple regression options available for modeling the wide range of dependent variables of importance to social work researchers. However, it does not follow from this that binary, multicategorical, or ordinal variables should be created from continuous variables or used when better continuous variables are available, or that censored variables should be used in place of variables that are not censored, or that truncated populations should be used in place of entire populations of interest. In many ways CLDV models provide approximations based on certain assumptions it would be better not to have to make. Many of these variables are referred to as "limited" for a reason. However, in numerous situations CLDVs are the best available dependent variables, and multiple regression models for CLDVs can provide the best available answers to our research questions. If we limit ourselves to a restricted range of multiple regression models, we might limit unnecessarily the range of dependent variables we model or misestimate the effects of our independent variables. ■

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An earlier version of this article was presented at a meeting of the Society for Social Work and Research, January 1999, Austin, TX. The National Institute of Mental Health, R24-NIMH53623, supported this work in part. The authors thank William H. Greene for his valuable suggestions on an earlier draft of this article.

Original manuscript received January 24, 2000
Final revision received August 28, 2000
Accepted November 6, 2000