To the Graduate Council:

I am submitting herewith a dissertation written by Carol Bruce entitled "Analytic Strategies for Data with Nonindependent Observations: Data Transformation, Structural Equation Modeling, and Information Criteria." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Human Ecology.

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ANALYTIC STRATEGIES FOR DATA WITH NONINDEPENDENT OBSERVATIONS: DATA TRANSFORMATION, STRUCTURAL EQUATION MODELING, AND INFORMATION-THEORETIC CRITERIA

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ABSTRACT

In studying the family, researchers tend to avoid using measures from multiple family members, as doing so violates the fundamental assumption of interdependence between observations. When multiple measures are used, the analysis is typically comparative, such as comparing the marital satisfaction of husbands and wives, or comparing academic achievement between siblings. While these approaches may be quite appropriate for particular research questions, it may also be the case that family researchers tend to fashion research questions to suit the analytic techniques available to them. This dissertation presents alternative analytic techniques to analyze data in the presence of observation interdependence. Three primary issues are addressed. First, the effect of observation interdependence on analytic results is explored, by simulating data with known parameters and increasing levels of observation interdependence at varying sample sizes. The data is analyzed and tabulated to reflect trends which appear in the estimates of regression parameters, sample variance, and the accuracy with which the correct model is produced in regression analysis. Second, five alternative techniques are tested using both the analysis of simulated data and real data from the National Survey of Children, to determine their effectiveness in regaining the analytic power lost in the presence of observation interdependence. Third, the author examines whether substantive results change with the use of different sampling strategies. A study conducted by Harris and Marmer (1996), using NSC data, is replicated and the results are compared when using multiple measures per family (with correction for observation interdependence), measures from the oldest child, from the youngest child, and from one target child chosen randomly. The author argues the importance of using multiple measures per family while correcting for the analytic impact of observation interdependence.

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CHAPTER 1

INTRODUCTION

Social science research often relies on traditional analytic techniques based on Fisher's classic hypothesis-testing model, seeking to identify relationships between variables. The analyst creates a null hypothesis which asserts that no such relationship exists. If the parameters of interest are large enough, relative to the parameter variance (or standard error), we are able to conclude that the relationships between the variables do indeed exist. The criteria for evaluating whether the parameters are large enough are based on knowing the theoretical distributions of the parameters. If the parameter estimates fall into a critical region of the parameter distribution, we conclude that these estimates did not occur randomly, and that they reflect a true association between the variables.

In testing estimates of population parameters, we typically assume that the data were selected randomly from a population with a normal distribution, and that certain parameters are thereby also normally distributed. In fact, the Central Limit Theorem allows us to presume that, regardless of the actual shape of the distribution in the population, the distribution of the standardized estimates of population means and regression coefficients will converge to a standard normal distribution when the sample is sufficiently large, and when the observations are independently selected and identically distributed.

In studying family phenomena, the assumption that the observations are

independently selected restricts the social scientist to a single observation for a given family. For example, if we are collecting data on fathers' involvement with their children and we wish to gather data on two children from each family, a father's involvement with one child may depend to some extent on his involvement with the other child, perhaps due to a parenting style which is relatively consistent across children. We would expect that a father who is highly involved with one child would also be highly involved with the other compared to fathers who exhibit low involvement overall. These observations would, therefore, fail to be independently selected. The result is referred to by several terms, e.g., observation interdependence, observation correlation, error correlation. In the study of family, the Central Limit Theorem thereby restricts sampling to a single observation per family, or it requires the researcher to make unrealistic assumptions of independence about observed behaviors we know are not likely to be independent. Violation of the assumption of independently selected random variables invalidates the Central Limit Theorem, yielding a non-normal parameter distribution. Many of our standard methods of analyzing such data would therefore yield inaccurate results, as they are predicated on the assumption of a normal parameter distribution. In fact, the χ^2, F, and t-distributions are all derived from the standard normal probability distribution which presumes independence between observations.

Under the condition of nonindependent observations, the true parameter distribution would more accurately be described as a conditional normal probability distribution. The conditional relationship would appear as follows:

$$P(x_2|x_1) = \frac{P(x_2,x_1)}{P(x_1)} \quad (1)$$

where $P(x_2|x_1)$ denotes the probability that the value x_2 would occur given that x_1 has occurred, x_2 denotes the father's involvement with his younger child, x_1 denotes the father's involvement with his older child, and $P(x_2,x_1)$ denotes the joint probability that both values would occur simultaneously. If x_2 and x_1 are independent of one another, then

$$P(x_2,x_1) = P(x_2) * P(x_1). \quad (2)$$

This would result in $P(x_1)$ cancelling out in equation (1) and the conditional probability of x_2 occurring given x_1 simply equals the probability that x_2 would occur, yielding the standard normal probability distribution. However, when the two cases are dependent upon one another, the marginal distributions are more complex, and the sample distribution a conditional probability distribution, where the probability of having selected an observation with a particular value depends upon our having selected another observation with a given value.

In the case of father involvement, the limitation posed by the Central Limit Theorem necessitates that the father's level of involvement overall be represented by his involvement with only one of his children. If the father is equally involved with all of his children then this limitation presents no difficulty. However, we might expect that a father would be more or less involved with a specific child, depending on such factors as the child's age, gender, disposition, or the compatibility between the father and child (Amato, 1987; Barnett & Baruch, 1987; Goldscheider & Waite, 1991; Harris & Morgan,

1991; Ishii-Kuntz, 1994; Marsiglio, 1991; Pleck, 1985, 1997; Volling & Belsky, 1991). In this case, we are not adequately representing this father's involvement with his children when we limit our measures to his involvement with only one child. We could create some aggregate measure of the father's involvement with his children; however, this would result in a loss of information where there is wide variance in father involvement between children.

Similar difficulties arise when we are examining the influence of family environmental variables on child well being. When we choose the well being of one child to indicate the effect of the family environment, we are misrepresenting the relationship between the variables to the extent that children have unique experiences in a common family environment (Rowe, 1994). In addition, we may anticipate that the same experiences within a common family environment could influence different children within the same family in a unique manner (Rowe, 1994; Brody 1998; Teachman, 1995, 1997). Thus, alternative analytic strategies which facilitate the analysis of data with nonindependent observations may increase the validity of family research by allowing the inclusion of multiple measures from a single family, as opposed to the usual approach of obtaining only a "cross-section" of the measure of interest by taking only a single measure per family, or constraining multiple measures into an aggregage or averaging form.

This argument raises three primary questions to be addressed in this dissertation. First, how and to what extent does correlation between observations influence analytic results? This question is examined by running iterations of regression analyses on

simulated data with known parameters. This analysis consists of a series of 100 iterations on data with increasing levels of observation correlation in 10 steps, and for varying sample sizes within each step (the modules for carrying out these analyses, written in MATLAB, are attached in Appendix 2). This approach will facilitate the examination of the influence of observation interdependence on the parameter distributions, as well as the frequency with which the correct model is produced within the 100 trials at each level of observation correlation for varying sample sizes.

Second, how might we take observation correlation into account as we analyze data? This study presents three primary alternative strategies and two additional variations for analyzing data with nonindependent observations, and tests the effectiveness of each method using the iterative strategy outlined above, noting the frequency with which each method identifies the correct model. Each analytic strategy is developed in detail in Chapter 3.

Lastly, what are the substantive implications of using multiple measures, as opposed to selecting a single observation per family? This question is examined by reconstructing an analysis carried out by Harris and Marmer (1996), using data from the National Survey of Children. These authors examined the presence of long-term effects of divorce using three waves of data, one taken when the children were between 7 and 11 years of age, one during the children's adolescence, and another during early adulthood. In the original study, they used data taken on two children per family (when more than one child was living in the household), but did not take correlation between the observations into account. The analysis is replicated in this study, taking observation

correlation into account using each of the proposed alternative methods. The analysis is then repeated using only one child per family. Three samples are drawn for analysis; the first using only the oldest child (of the two children included in the sample), the second using the youngest child, and the third selecting one child per family randomly. The outcome for each sampling strategy are then compared to examine whether critical information is lost by restricting our samples to a single observation per family, which is the current standard practice in most family research, as will be detailed in Chapter Two.

CHAPTER 2

LITERATURE REVIEW

As indicated in the introduction, this study is focused on three primary issues: 1) How does dependence between observations affect analyses which presume normal distribution; 2) How can this type of data be more accurately analyzed; and 3) How does the use of multiple measures, as opposed to single measures, per family influence analytic results? While there is not a great deal of literature which directly deals with these issues, particularly in the family sciences, scientists in other disciplines have been quite aware of the issues and have made significant advances toward dealing effectively with the inherent analytic difficulties associated with observation interdependence. In addition, there are selected studies in the family literature which give us some clues as to what we might expect to find when we use multiple measures per family, and when we take observation correlation into account when multiple measures are used. Each of these discussions in the literature will be reviewed below.

Analytic Approaches to Accounting for Observation Interdependence

Most of the attention to the problem of accounting for correlation between observations has arisen from fields of discipline beyond family science. Observation interdependence is often addressed in statistics texts in the context of regression analysis, where its effect becomes apparent through correlated errors. Economists frequently encounter correlated errors, as their phenomena of interest typically occur as a function of time (Myers, 1990). For example, in examining factors which produce variation in the Gross National Product, economists find that the GNP does not fluctuate randomly from

one year or quarter to the next, but that its value at one point in time is typically influenced by its value at a previous point in time. This association between observations is addressed by creating lagged variables, where each value of the variable is grouped with one or more previous values with which it is expected to be associated. These lagged variables then serve as additional predictors in the regression equation, a technique known as autoregression.

Cultural anthropologists often encounter observation interdependence in studying cultures which share geographic proximity (Simonton, 1975). They find that the phenomena observed in a particular culture are often more similar to nearby cultures than to those which are more geographically distant, a phenomenon known as spatial autocorrelation. Simonton proposes that observation correlation results in an inflation of the degrees of freedom, as some of the variable values are, in effect, fixed because they are in some way determined by other values. He proposes that the analyst determine the number of nonredundant observations, and adjust the degrees of freedom accordingly.

Naroll (1970), also a cultural anthropologist, addresses the same issue with a different approach. He suggests that the analyst first determine the "measure of similarity" between observations by establishing the level of correlation between observations on the outcome variable. These correlations are then used to partial out the effect of the observation interdependence in a partial correlation analysis, which effectively controls for the error correlation.

From the field of demography, Loftin and Ward (1983) recognized the influence of spatial autocorrelation in their study of the influence of population density on fertility

rates. They pointed out that ignoring the influence of spatial processes in analyzing geographical units produces incomplete models and misleading results. They employed an autoregressive model to account for spatial processes, and found no relationship between population density and fertility rates, although such a relationship had been established in previous studies which had failed to control for spatial autocorrelation.

In summary, we find that the issues associated with observation interdependence have long been recognized in other social science disciplines, where the association occurs as a function of observation sharing a time or geographic space reference. The same issue in family sciences involves an association as a function of shared social group.

Observation Interdependence in the Family Sciences

While the issue of observation interdependence has become well-integrated in many of the social science disciplines, the analytic and methodological issues surrounding the use of multiple measures per family have received little attention in the family research literature. Most graduate-level texts on research methodology in the family sciences ignore the issue altogether (Bickman & Rog, 1991; Black, 1998; Fowler, 1993; Miller, 1986; Miller, 1991; Weisberg, 1996). Others note that taking multiple measures per family would create analytic difficulties, and advise that this methodology should either be avoided or that the data should be subjected to paired or grouped analysis, such as paired t-tests or repeated measures analyses of variance (Copeland & White, 1991).

The appropriateness of these approaches would depend on the research question. If the phenomenon of interest does not vary widely within the family, then taking only one measure within each family may be appropriate. Using a single measure per family

might also be appropriate if the analyst is interested only in studying phenomena associated with family members with very specific targeted characterics, such as an interest in children of a particular age group or birth order status. The option of using paired analysis would be appropriate if the analyst is interested in making comparisons between family members, such as a comparison between children based on their gender or between spouses. However, we must guard against fashioning our research questions to fit our analytic techniques. Rather, we need to develop the techniques which will allow us to ask the questions in which we are truly interested, and to employ all of the information available to us in answering these questions.

The Journal of Marriage and the Family produced a special issue in November 1982 devoted exclusively to methodological issues in the study of the family. Miller, Rollins, and Thomas (1982) discussed the importance of obtaining measures from multiple family members at length. They argued that family cannot be adequately assessed using measures of individuals, and that the use of measures from multiple family members can increase both the reliability and validity of our measures. They went on to point out that, although most researchers recognize the benefits of using measures from multiple family members, they are constrained by the analytic difficulties that arise from correlated error in data of this type.

While this issue has been largely ignored in the family literature, Teachman, Carver, and Day (1995) conducted a notable study which addressed the problem directly, and presented an innovative technique for analyzing data under these conditions. The authors used data on pairs of siblings from the High School and Beyond study, to

examine whether family environmental factors influence children's mental ability and grades. They argued that it was important to include multiple measures per family on the grounds that, in failing to do so, we are in effect drawing conclusions about families (which represent one level of analysis) from the examination of individuals (which represents another level of analysis). Therefore, in order to draw conclusions about families, we need to make every effort to assess the family, rather than a single individual within a family. They analyzed the data using a structural equation model whereby the family environmental variables predicted family outcomes, with the outcomes for each sibling loading on a single family outcome construct. The covariance parameter for the error terms associated with sibling outcomes, were then left unconstrained, and the model was estimated taking this covariance into account.

While there has been very little attention to this issue in the family sciences, it is heartening that some scholars have attended to it and have developed a method for dealing with the analytic difficulties which appears to be quite promising. Teachman et al's method will be tested in this study and the results provided in Chapter 4.

Measures from Multiple Family Members

The fact that we have been restricted to single measures per family by a lack of analytic techniques to deal with error correlation has prevented us from directly addressing the impact of measures of multiple family members on analytic results. Although we may anticipate on theoretical grounds that using multiple measures per family will provide more valid and reliable measures, we have not yet been able to test this proposition. In fact, it is likely that we will find that multiple measures per family are

more or less useful depending on the phenomena being assessed and the questions being asked.

There are instances where the phenomenon of interest is truly a function of the individual, although it has implications for family. For example, Thornberry, Smith, and Howard (1997) examined the relationship between various sociodemographic predictors, and youth risk for becoming a parent in adolescence. Although adolescent parenthood is certainly a family issue, in this context youth risk is a property of the individual. However, the risk could be assessed as a function of family variables (such as the age at which the adolescents' parents first bore children, the child's emotional closeness to the parents, the extent to which he or she identifies with the parent, the adolescent's educational and professional aspirations, etc.), and in this case it would be appropriate to assess all family members within the targeted age range.

While some family issues may be appropriately addressed by studying phenomena on an individual level, others are most appropriately examined as a function of family. Pong's (1997) study of the effect of family and school factors on students' academic achievement presents an interesting example of how results may change with the use of measures from multiple family members. This author restricted the study to the analysis of academic outcomes only for eighth-grade students, effectively restricting the sample to measures on a single individual per family. However, there is no apparent theoretical basis for restricting the analysis to eighth-grade students. In fact, if we are interested in understanding the influence of family factors on children's academic performance, it would be most appropriate to examine the academic performance of all children within a

given family, as it is possible that the same family factors influence the children within a single family differently. The father's level of education may be quite influential on the child's academic performance if that child closely identifies with the father, but have little effect on a child who more closely identifies with the mother. It is also possible that children within a particular family experience that family in a unique fashion. For instance, in this study the author looks at the amount of discussion that takes place between the parent and child on school matters. This factor is likely to vary depending on the child's age, the quality of the relationship between the parent and child, and the child's temperament. Finally, even if all children within a particular family had identical experiences within that family, and were influenced by these experiences in an identical manner, it is likely that there are additional factors which may influence academic achievement which are unique to the child. Certainly, we should find that children's intelligence will vary within a family, or that the particular areas in which children from one family excel will vary. While one child may be very good at math, another may excel in artistic pursuits. There are numerous ways in which children within a particular family may vary from one another, and numerous explanations for these differences. We cannot accurately assess the influence of family on child outcomes by examining these processes for only one child from a given family (Rowe, 1994).

A second issue arises from Pong's (1997) study which has implications for the analysis of data with interdependent observations. In addition to family variables, Pong examined the influence of school variables on students' academic achievement. The theoretical premise was that, as constituent members of a school community, parents will

exert an aggregate effect on the school environment, as their characteristics impact on their children, which then alters the character of the student body as a whole. The methodological practice of restricting a sample to measures of a single individual per family is akin to the analyst being restricted to choosing only one child per school for this analysis. Certainly, including multiple children from a particular school, as this study does, creates observation interdependence. While restricting the sample to only one child per school would eliminate this analytic difficulty, it would make little sense to expect that one child from a large student body could adequately represent the influence of school factors on student academic achievement for all of the students within that particular school. By the same reasoning, it makes little sense to expect that one child from a particular family will adequately represent the influence of family factors on child outcomes for all of the children within that particular family. This practice has arisen largely from our inability to account for the error correlation that results from interdependence between observations. Appropriate analytic techniques should eliminate these difficulties and facilitate more valid measures of family processes.

Impact of Observation Interdependence on Analytic Results

While it is generally recognized that the existence of an association between observations invalidates the Central Limit Theorem, there has been little discussion of exactly how this condition affects analytic results. Simonton (1975) suggests that the presence of autocorrelation results in an overestimation in the degrees of freedom. In this case, we would find that our statistical criteria for assessing parameter estimates, the value from the t-distribution, would be underestimated. This would result in our failing

to reject a false null hypotheses, committing a Type II error.

This sort of reasoning is also useful in considering the possible effects of observation interdependence on the variance of an outcome variable. When we include measures from multiple family members without accounting for dependence between the observations, we are in effect overestimating the variance. While this effect is demonstrated mathematically in Chapter 3, we can establish it at this point inductively. When the value of one observation depends to some extent on the value of another observation, the first observation is not truly free to vary. In other words, its variance is restricted. If we fail to take this fact into account, we are in effect overestimating the variance. When observation correlation is not taken into account, the variance is biased as follows:

$$\text{biased variance} * (1-r^2) = \text{unbiased variance}$$

or,

$$\text{biased variance} = \text{unbiased variance}/(1-r^2)$$

where "r" represents the correlation between observations. When r^2 is small, there will be little effect on the estimate of the sample variance, but when observation correlation is high, there will be a correspondingly large bias in the sample variance estimate.

The analytic consequence of overestimating variance is a reduction in the power of our analysis. If the sample variance is overestimated, the standard error of our parameter estimates are also overestimated, thus the t-statistic is underestimated. We then increase our chances that the t-statistic will fail to fall within the critical region, thus increasing our risk of failing to reject a false hypothesis, again committing a Type II error.

Although some large-scale national studies have collected data with measures from multiple members per family, analysts tend to use this data without correcting for the resulting association between observations. Several studies from the National Survey of Children are carried out in this way. However, the fact that the analyst failed to correct for observation interdependence does not necessarily invalidate the study's results. A reduction in power will alter the study's conclusions only if the effect sizes are such that their significance could change with a moderate increase in analytic power.

We can roughly estimate the ways in which a study's results would change by reasoning through a series of related steps: 1) What t-value would render a particular parameter significant; 2) What standard error would yield this t-value; and 3) What level of observation correlation would yield this standard error following correction? The t-value that would render a parameter significant is obtained from probability distribution tables, typically approximately 1.65 for a two-tailed t-test with samples over 60. The standard error which would yield this t-value is then obtained as follows:

standard error = parameter estimate/t-value at (p=.05).

If we consider this standard error to be the unbiased standard error, we can calculate what level of error correlation would yield this unbiased standard error upon correction as follows:

$1-r^2$ = unbiased standard error/biased standard error

For marginal effect sizes, even relatively low threshold levels of observation correlation may lead to significant effects once observation correlation is taken into account.

Furstenberg and Teitler (1994) used data from the NSC to identify factors which

mediate the relationship between divorce and negative outcomes for children. The effect sizes for the predictors in this study were all quite large, with the standardized regression coefficients ranging from .51 to .96, and those which failed to be significant were quite small, ranging from .07 to .20. The results of this study are strong enough that they would probably not be changed when the observation correlation is taken into account in data analysis.

The findings of Zill, Morrison, and Coiro (1993) appear to be more sensitive to the observation interdependence. Zill et al (1993) used the NSC data to examine long-term consequences of divorce for children. Part of their analysis involved a comparison of children whose mothers had and had not remarried on negative outcomes. Only two of nine comparisons proved to be significant, with more children whose mothers had remarried exhibiting behavior problems in adolescence and reporting poor relationships with their fathers in young adulthood. As the comparisons were only significant on two outcomes, these findings appear to be relatively minor, and receive very little attention in the discussion. Several of the reported t-statistics on the other outcomes are quite close to significance, but fall short. Accounting for observation correlation at the following levels would likely result in significant t-statistics: 1) There would be a significantly larger proportion of children whose mothers had not remarried reporting poor relationships with their fathers in adolescence assuming observation correlation of only .08; 2) There would be a significantly larger proportion of children whose mothers had remarried reporting poor relationships with their mother in young adulthood assuming observation correlation of only .15; and 3) There would be a significantly larger proportion of children whose

mothers had remarried exhibiting behavior problems in young adulthood assuming observation correlation of only .09. If observation correlation had been taken into account in this analysis, it is likely that five of the nine comparisons between children whose mothers had and had not remarried would have proven significant. The results suggest that, generally, children whose divorced mothers remarry fare worse than those whose mothers remain unmarried following divorce. This is an important finding, as researchers tend to find that remarriage improves the emotional wellbeing of divorced adults and the economic wellbeing of children. While this may be true, it also appears that remarriage has some negative influence on the emotional and social wellbeing of children.

The estimated analytic consequences of failing to account for observation correlation is even more dramatic in Harris and Marmer's (1996) study of the role of parental involvement in ameliorating the negative effect of poverty on adolescent wellbeing. While their results indicated that the mother plays a significant role in buffering the negative effects of poverty for children on all of four possible outcomes, the fathers' involvement was a significant buffer on only one of the four possible outcome variables. Their conclusion was that the mother plays a more important role in ensuring the wellbeing of children living in poverty, and that the father's role is relatively inconsequential. However, using the method outlined above, we find that several effects which appeared to be substantial but insignificant may reach significance when observation correlation is taken into account. In fact, we can anticipate that: 1) Fathers' behavioral involvement would significantly influence youth attainment for persistently poor families assuming observation correlation of merely .01, and for families receiving

welfare assuming observation correlation of at least .12; 2) Fathers' behavioral involvement would influence youth delinquency for temporarily poor families assuming observation correlation of only .08, for persistently poor families assuming observation correlation of at least .24, and for families receiving welfare assuming observation correlation of at least .28; 3) Fathers' emotional involvement would influence youth depression for temporarily poor families assuming observation correlation of only .04, and for families receiving welfare assuming observation correlation of only .09; and 4) Fathers' emotional involvement would influence the occurrence of teen pregnancy for families receiving welfare assuming observation correlation of only .01. These potential results would dramatically change the conclusions of this study, and might have a critical impact on the formation of public policy. Thus, the results of a replication of this study will be examined more closely in Chapter 4 of this study.

Summary

Although the literature dealing with the issue of observation interdependence is sparse, the current body of social science research offers a few clues as to what we might expect to find in this study. We first find that the observation correlation which occurs as a result of using measures from multiple family members is analytically similar to that which occurs in economic studies which find autocorrelation as a function of time, and anthropological studies which find spatial autocorrelation as a function of shared geographic space. Thus, the techniques used in these fields, specifically autoregression, should prove useful in accounting for the observation correlation arising from measures of multiple family members. This technique will be tested and the results presented in Chapter 4.

Second, we find that while there are family issues which are appropriately studied as a function of individuals, we tend to fall back on using measures for single family members largely because we do not have the analytic techniques to account for the resulting observation correlation otherwise. It is important, therefore, that we develop the analytic techniques which will facilitate the examination of research questions in which we are truly interested, using the most appropriate measures.

Finally, the current literature indicates that many analysts who use measures from multiple family members fail to account for the resultant observation correlation. When the effect sizes are relatively large, but statistically insignificant, it is likely that they would become significant if the analyst were to control for the observation correlation. This hypothesis will be tested more directly in Chapter 4, using the analysis first presented by Harris and Marmer (1996).

CHAPTER 3

METHODOLOGY

This dissertation presents three primary strategies which facilitate the analysis of data with nonindependent observations. The first approach involves a transformation of the conditional data so that it follows the standard normal distribution, allowing the use of classical hypothesis testing criteria. The variable transformation is developed below using classical mathematical statistics theory. The second approach employs a structural equation model incorporating the expected covariance between observations. The regression weights are then estimated taking the dependence between observations into account. The third approach employs the data "as is" and uses standard analytic techniques, however, the final models are evaluated using an information theoretic criterion which accounts for dependence between the residuals.

Data Transformation

When observations within a given data sample exhibit bivariate dependency, the distribution should be modeled as a conditional probability distribution, whereby the probability of x_2 occurring is conditioned upon the fact that x_1 occurred. The development of this model requires the creation of two variables: (1) the first contains the measures taken for each member of the family; and (2) the second pairs each observation for the first variable with the observation upon which it is dependent. In the example of father involvement, the father's involvement with child 1 (variable 1) is paired with the father's involvement with child 2 (variable 2). This is followed by pairing the father's involvement with child 2 (variable 1) with the father's involvement with child

Case Number	Variable 1	Variable 2
1.0	inv-child1-case1	inv-child2-case1
1.5	inv-child2-case1	inv-child1-case1
2.0	inv-child1-case2	inv-child2-case2
2.5	inv-child2-case2	inv-child1-case2
3.0	inv-child1-case3	inv-child2-case3
3.5	inv-child2-case3	inv-child1-case3

Figure 1. Creation of Dependent Pairs of Involvement Measures

1 (variable 2). Figure 1 illustrates how this assignment would proceed.

This example assumes that we have taken two measures from each family. Of course, we could take as many measures as are available, and the pattern would remain the same; creating "k" new variables, where k is equal to the number of measures taken per family.

Derivation of the Conditional Probability Distribution

The conditional probability distribution is derived by dividing the joint probability distribution by the marginal probability distribution of the determining variables, as indicated in Equation (1). In the case of bivariate dependency, the marginal probability distribution involves only one variable labeled x_1. The joint probability distribution is modeled as a bivariate normal distribution, while the marginal distribution of x_1 is modeled as the univariate normal probability distribution:

$$P(x_2|x_1) = \frac{P(x_2,x_1)}{P(x_1)} = \frac{(2\pi\sigma^2)^{-1}(1-\rho^2)^{-.5}\exp-((2\sigma^2(1-\rho^2))^{-1}((x_2-\mu)^2-2\rho(x_2-\mu)(x_1-\mu)+(x_1-\mu)^2))}{(2\pi\sigma^2)^{-.5}\exp-((2\sigma^2)^{-1}(x_1-\mu)^2)}$$

$$= (2\pi\sigma^2(1-\rho^2))^{-.5}\exp-(((2\sigma^2(1-\rho^2))^{-1})((x_2-\rho x_1)-\mu(1-\rho))^2) \qquad (3)$$

where ρ denotes the correlation between x_2 and x_1.

Close examination of equation (3) reveals that the conditional distribution of x_2 appears to be a normal distribution where

$$x_t = x_2-\rho x_1 \qquad (4)$$

$$\text{mean}(x_t) = \mu(1-\rho) \qquad (5)$$

$$\text{variance}\ (x_t) = \sigma^2(1-\rho^2), \qquad (6)$$

with x_t representing a transformation of the variable x. We can determine if this is indeed the case using the moment generating functions, which will produce the formulas for the population mean and variance of the distribution of x_t. The mean and variance for x_t ($=x_2-\rho x_1$) are defined by the first and second derivatives, respectively, of the moment generating function (equation 7), when t is equal to zero.

$$\psi(t) = \exp\ (\mu(1-\rho)t + .5\sigma^2t^2\ (1-\rho^2)) \qquad (7)$$

$$\frac{\partial}{\partial t}(\psi(t)) = [\mu(1-\rho) + \sigma^2t(1-\rho^2)]\exp\ (\mu(1-\rho)t + .5\sigma^2t^2(1-\rho^2))$$

$$\text{mean}(x_t) = E(x_t) = \frac{\partial}{\partial t}\psi(t)|_{t=0} = \mu(1-\rho) \qquad (8)$$

$$\frac{\partial^2}{\partial t}(\psi(t)) = [(\mu(1-\rho) + \sigma^2t(1-\rho^2))^2\exp\ (\mu(1-\rho)t + .5\sigma^2t^2(1-\rho^2))] + [(\sigma^2(1-\rho^2))\ \exp\ (\mu(1-\rho)t + .5\sigma^2t^2(1-\rho^2))]$$

$$\text{Var}(x_t) + (E(x_t))^2 = E(x_t)^2 = \frac{\partial^2}{\partial t}\psi(t)|_{t=0} = (\sigma^2(1-\rho^2)) + (\mu(1-\rho))^2 \qquad (9)$$

$$\text{Var}(x_t) = \sigma^2(1-\rho^2) \qquad (10)$$

Equations (8) and (10) confirm that $x_t=x_2-\rho x_1$ does indeed follow a normal distribution, with the mean and variance formulated as indicated in equations (5) and (6).

The maximum likelihood estimates for the population mean and variance are

derived as follows:

$$L(\mu,\sigma^2) = (2\pi\sigma^2(1-\rho^2))^{-n/2}\exp(-1/(2\sigma^2(1-\rho^2)))\Sigma((x_t-\mu(1-\rho)))^2$$

$$\ln(L(\mu,\sigma^2) = (-n/2)\ln(2\pi)-(n/2)\ln(\sigma^2(1-\rho^2))-(2\sigma^2(1-\rho^2))^{-1}\Sigma((x_t-\mu(1-\rho))^2$$

$$\frac{\partial\ln(L(\mu,\sigma^2))}{\partial\mu(1-\rho)} = \frac{n\mu(1-\rho)-\Sigma x_t}{\sigma^2(1-\rho^2)}$$

By setting the first derivative of the natural log of the maximum likelihood function with respect to the mean equal to zero and solving for $\mu(1-\rho)$, we attain the following result:

$$\mu(1-\rho) = \frac{\Sigma x_t}{n} = \bar{x}_t. \tag{11}$$

The maximum likelihood estimate for the sample variance is derived by taking the first derivative of the natural log of the maximum likelihood function with respect to $\sigma^2(1-\rho^2)$, setting the result equal to zero, and solving for the variance as follows:

$$\frac{\partial\ln(L(\mu,\sigma^2))}{\partial\sigma^2(1-\rho^2)} = \frac{-n}{2\sigma^2(1-\rho^2)} + \frac{\Sigma(x_t-\mu(1-\rho))^2}{2(\sigma^2(1-\rho^2))^2} = 0$$

$$\sigma^2(1-\rho^2) = \frac{\Sigma(x_t-\mu(1-\rho))^2}{n} \rightarrow \frac{\Sigma(x_t-\bar{x}_t)^2}{n} = s_t. \tag{12}$$

This establishes that when the following transformation is performed:

$$x_t = x_2 - rx_1, \tag{13}$$

where r equals the sample correlation between x_1 and x_2, x_t will follow a univariate normal distribution, and furthermore, that the standard formulas for estimating the population means and variances can be applied directly to the transformed data without modification.

The derivations outlined above are based on data sets with bivariate dependency. If we were to take all measures available from each family, we would be faced with

accounting for dependency between three or more observations from a single family. This requires the derivation of an appropriate variable transformation using a multivariate normal probability distribution. The derivation is far more complicated than that which is outlined above, and is therefore attached in Appendix I.

Closer examination of Equation (13) suggests an extension of the data transformation method which may also produce good results. Our predictive model using the transformed variable is

$$y_t = \beta \mathbf{x}$$

$$y_2 - ry_1 = \beta \mathbf{x}$$

$$y_2 = \beta \mathbf{x} + ry_1$$

This reformulation of the predictive model suggests that the data transformation simply creates an autoregressive model where the parameter for the paired y-variable is estimated a priori to be equal to $r_{y1,y2}$. It would therefore be informative to analyze the untransformed data with interdependent observations using the paired y-variable as an additional predictive variable. The parameter for y_p would then be estimated using least squares, which may produce better results than would be obtained through an a priori transformation of the y-variable.

Structural Equation Modeling

The second approach for analyzing data with nonindependent observations involves constructing a structural equation model which takes the dependence between the observations into account. One way to do this would be to construct k-variables for each of the relevant indicators as illustrated in Figure 1. The model would then estimate

the regression weight for the latent construct on each original indicator (variable 1) and its paired observations (variable 2). Suppose that we are employing a scale which contains three items (p=3) and that the sample contains observations with bivariate dependence (k=2) (Figure 2).

We are interested in estimating the parameters in the following equation:

$$\mathbf{y} = \Lambda_y \eta + \epsilon. \tag{29}$$

In constructing a measurement model, we are particularly interested in the value of the regression weights, Λ_y, which will establish the extent to which each indicator loads on the latent construct. In structural equation modeling, the regression weights are estimated via a regression on the covariance matrices of the observed and latent variables.

$$\Sigma_y = \Lambda_y \phi \Lambda_y' + \Theta_{\epsilon}. \tag{30}$$

When there is no dependence between the observations, the off-diagonal elements of the covariance matrix for the model errors (Θ_ε) would be equal to zero. In our example, with three indicators and two groups of variables reflecting a bivariate dependency, the error covariance matrix would appear as follows:

$$\begin{array}{llllll}
[[\theta_{\epsilon 11} & \theta_{\epsilon 12 \epsilon 11} & 0 & 0 & 0 & 0] \\
(31) & & & & & \\
[\theta_{\epsilon 12 \epsilon 11} & \theta_{\epsilon 12} & 0 & 0 & 0 & 0] \\
[0 & 0 & \theta_{\epsilon 21} & \theta_{\epsilon 22 \epsilon 21} & 0 & 0] \\
[0 & 0 & \theta_{\epsilon 22 \epsilon 21} & \theta_{\epsilon 22} & 0 & 0] \\
[0 & 0 & 0 & 0 & \theta_{\epsilon 31} & \theta_{\epsilon 32 \epsilon 31}] \\
[0 & 0 & 0 & 0 & \theta_{\epsilon 32 \epsilon 31} & \theta_{\epsilon 32}]].
\end{array}$$

The regression weights are therefore estimated as a function of the variances of the observed variables and latent constructs, the covariances between the observed variables,

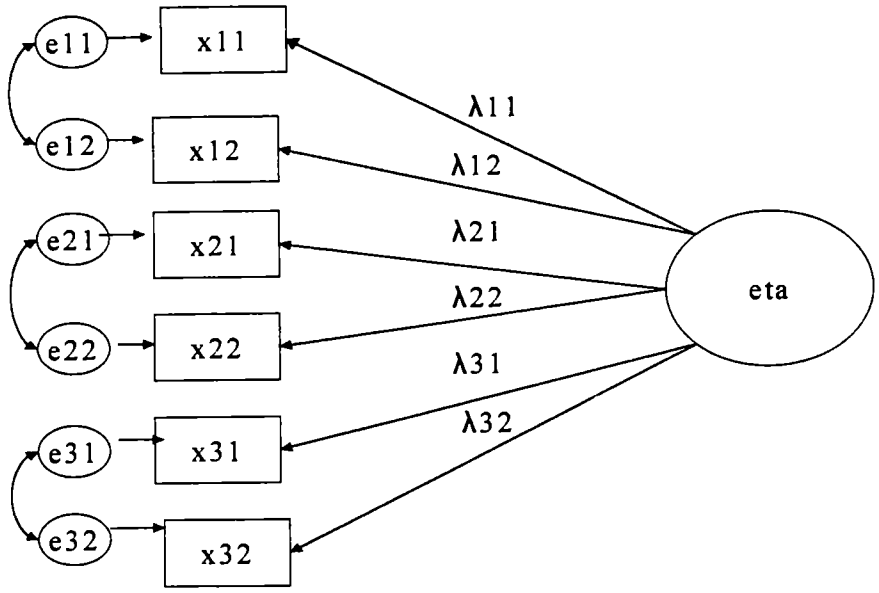

Figure 2. **Structural Equation Model Incorporating Error Covariance (k=2, p=3)**

and the variances and covariances of the residuals.

The inclusion of the covariance between the residuals for the bivariate dependent observations introduces new parameters to be estimated in the model. This needs to be taken into account as a potential problem for model identification. In the bivariate case, the model will be identified when a minimum of three indicators are employed to define the latent construct. In this case there will be 21 constants to estimate 16 unknown quantities.

Information Complexity Criterion

The third approach to analyzing data with dependent observations employs information theoretic criteria as an alternative to classical hypothesis testing. Akaike (1973) pioneered the use of information theoretic criteria as an alternative to classical

hypothesis testing in statistical analysis. His criteria, AIC, is formulated by assessing the extent to which a proposed model fails to fit given sample data, using the natural log of the maximum likelihood function multiplied by a factor of -2. The lower this figure is, the better the model fits the data. The figure is then penalized by twice the number of parameters included in the model, in order to favor more parsimonious models, or those models which provide the best fit with a minimum number of parameters.

$$AIC=(-2*\ln(L(\theta))) + 2*m \tag{32}$$

As the first component of this criterion measures lack of fit, we would expect that any lack of fit occurring due to misspecification of the model will be apparent across all possible subsets of predictors. The correlation between observations on the outcome variable should be constant regardless of which predictors are incorporated into the model. Thus, AIC should prove to be a reasonable criterion for evaluating regression models when there is error correlation present.

Bozdogan (1990) extended Akaike's work in developing ICOMP as an alternative information-theoretic criterion. ICOMP is also based on the maximum log likelihood function, but extends the penalty factor from one based only on the size of a model to one which accounts for the number of parameters, the precision of the parameter estimates, and interdependence between parameter estimates and among residuals. As such, this technique may present an improved method for selecting the best model for data with nonindependent observations.

The penalty factor for ICOMP may be derived from the Inverse Fisher Information Matrix, or from the finite sampling distributions of the parameter estimates.

The technique employed in this dissertation will employ ICOMP using the finite sampling distribution of the parameter estimates. The formula for ICOMP applied to multiple regression appears as follows:

$$\text{ICOMP} = (-2*\ln(L(\theta))) + C_1(\text{Cov}(\theta)) \tag{33}$$

where $C_1(\cdot)$ represents the complexity of the variance-covariance matrix of the parameter estimates. The first term in equation (33), representing the proposed model's lack of fit, is operationalized as follows:

$$\text{Lack of fit} = (n*p*\ln(2\pi))+(n*\ln(\det(\Sigma)))+(n*p) \tag{34}$$

where p equals the number of dependent variables and Σ represents the squared residual matrix (E'*E) with dimensions p by p. The complexity term is represented by two terms, one reflecting the complexity of the covariance matrix of the regression coefficients and another reflecting the complexity of the covariance matrix for the residuals. These terms are then operationalized as follows:

$$C_1(\Sigma_\beta) = (((q*p)/2)*(\ln(\text{trace}(\Sigma_\beta)/(q*p))))-((1/2)*(\ln(\det(\Sigma_\beta)))) \tag{35}$$

$$C_1(\Sigma_\epsilon) = n*[(((p)/2)*(\ln(\text{trace}(\Sigma_\epsilon)/(p))))-((1/2)*(\ln(\det(\Sigma_\epsilon))))] \tag{36}$$

where q equals the number of independent variables, Σ_β represents the covariance matrix of the regression coefficients, and Σ_ϵ represents the covariance matrix of the residuals. It is the latter matrix which has the potential for accounting for dependence between observations.

In the case of multivariate regression, the covariance matrix for the residuals will be a p by p matrix which reflects both the amount of variance in and the amount of covariance between prediction errors for each dependent variable. If the observations are not

independent, we can model the dependency within this matrix. We begin by creating additional vectors which lag the residuals by one. This procedure is repeated until we have created "n" new residual vectors. A new residual matrix is then created by combining the original and the newly created residual vectors, and the covariance matrix for these vectors is then calculated. The resulting matrix is substituted for Σ_ϵ in equation (36), and will now account for both the interdependence between residuals for each independent variable and the interdependence between observations.

Candidate models are generated through the selection of all possible subsets of potential predictors. The superior model is that for which ICOMP is minimized. This will occur when a model provides a decrease in the lack of fit to a degree which exceeds the increase in model complexity which results with the addition of parameters. The ICOMP criteria will automatically account for the dependence between observations through the covariance of residual errors for each candidate model.

Summary

The theoretical assumptions of the Central Limit Theorem places methodological constraints on family researchers such that analyses are often restricted to the observation of only one member per family. When multiple family members are included, the study is typically designed to make comparisons between family members. These constraints are problematic when there is significant variation in a particular phenomenon within families. Restricting a sample to include one member per family results in a loss of information in this case, which may lead to very different conclusions than would be obtained if measures from multiple members per family were included in the analysis.

Thus, it is necessary to develop analytic alternatives which facilitate the analysis of data with nonindependent observations.

In this dissertation, five analytic alternatives are developed for this purpose. These techniques fall into three "families" of analytic techniques. The first two approaches, data transformation and autoregression, are based on an analysis of variance in the outcome variable, and determination as to the proportion of variance which is accounted for by the explanatory variables. The third, structural equation modeling, is based on establishing a relationship between the covariance structures of the observed variables and latent constructs and between the latent constructs. These latent constructs represent the observed variables minus measurement error. The fourth and fifth approaches arise from information theory. They are based on an assessment of model fit using the maximum likelihood function. As these techniques take three very different approaches to data analysis, they should produce slightly different results as we attempt to correct for observation interdependence. The effectiveness of each approach is evaluated under varying conditions of error correlation and sample size, while also exploring the necessity of employing alternate analytic techniques under these conditions.

CHAPTER 4

RESULTS

We begin by examining the ways in which correlation between observations influences analytic results, using iterations of regression analyses on simulated data with increasing levels of observation correlation. These analyses are followed by testing the alternative strategies for analyzing data with nonindependent observations by correcting or accounting for observation interdependence. Finally, the best analytic strategies are employed to reanalyze the models presented in Harris and Marmer (1996), while also testing for the effects of various sampling strategies.

The Influence of Observation Correlation on Analytic Results

This analysis begins with first creating sets of 100 samples, characterized by varying sample size (N=50, 100, 200, 500) and by the level of error correlation (r=.00-.90), resulting in a total of 4,000 samples. These four sample sizes were selected to reflect the small, moderate, and large sample sizes typically encountered in family research. Although there is an increasing presence of analysis of large national data sets in the family literature, with thousands of observations, it was concluded that a sample size of 500 was large enough for the purposes of this study. It is anticipated that a sample size of 1,000 or more would simply yield more analytic power overall, but the pattern of influence of observation interdependence should be essentially the same.

The samples were created in MATLAB by first generating five vectors of randomly generated numbers (four that would become the predictor variables, and one for the random error) from a standard normal distribution. The dependent variable was created

as a function of three of the four independent variables and the random error. The regression equation reflecting the "true" relationship between the variables would be:

$$y=(.00*x_1) + (.05*x_2)+(.25*x_3)+(.75*x_4)+e_y \ .$$

The predictor variables and errors were standardized so that the regression coefficients will represent standardized beta weights, thus preserving the relative strengths of influence for the predictors. Thus in the population, the true nature of the relationships between the predictors and y are such that x1 is not related to y, x2 is weakly related to y, x3 has a moderate influence on y, and x4 has a strong relationship with y.

In the absence of observation correlation, we would expect to find that the model which would be produced in regression analysis would vary by sample size. At the smaller sample sizes, it is unlikely that the weak influence of the second predictor on y would be detected, and that at very small sample sizes (N=50), the third predictor may not be included either. The larger sample sizes should be able to detect the influence of the third predictor, but may still fail to detect the weak effect of the second predictor in most cases. Therefore, the "true" model, that containing the second, third, and fourth predictors, is actually not expected to be the predominant model produced, due to the inherent limitations of developing models of populations based on inferences from samples.

The impact of observation correlation should be indicated by a tendency to select the "incorrect" model. As it is anticipated that observation correlation reduces analytic power, we should find that regression analyses will increasingly tend to favor the simpler models containing the stronger predictors as observation correlation increases.

Observation correlation was induced by creating dependence between adjacent pairs of residuals or error terms:

$e_y = e_{y1} + (corr * e_{y2})$.

The MATLAB program was written so that the analyst could input the level of error correlation (corr) to be tested. Thus 100 samples were generated at a level of error correlation of .00, of .10, and so on up to a level of .90. This was repeated for each of the four samples sizes. Regression analyses were then performed, creating vectors of the parameter estimates, and indication as to which parameters proved to be statistically significant.

In Tables A-1through A-4 in Appendix III (pp. 93-94), we compare the mean beta parameter estimates in column 1 (samples with no error correlation) to those in columns 2 through 9 (samples with increasing error correlation). These are followed by Tables 5-8 (pp. 95-98) which indicate the number of times in 100 trials, at each level of error correlation, that a particular model was produced, with each table providing the results for a particular sample size. Examination of these tables yields two interesting patterns.

First, it is apparent from the tables that the parameter estimates are increasingly underestimated as the level of error correlation increases. For the smaller sample sizes, in Tables 1 and 2, this pattern is most apparent for B_3 and B_4. When N=50, B_3 is reduced by 13% (from .198 at r=.00 to .173 at r=.90) and B_4 is reduced by 17% (from .584 at r=.00 to .487 at r=.90) at the highest level of error correlation. At N=100 B_3 is reduced by 22% and B_4 reduced by 18% at the highest level of error correlation.

With the larger samples, this pattern is apparent for B_2, as well as B_3 and B_4

(Tables A-3 and A-4). At N=200, at the highest level of error correlation, B_2 is reduced by 17%, B_3 by 13%, and B_4 by 19%. For the largest sample, where N=500, B_2 is reduced by 21%, B_3 by 17%, and B_4 by 18%. Generally, it appears that observation correlation results in an underestimation of regression parameters.

A second pattern emerges from examination of Tables A-5 through A-8. In Table A-5, with N=50, we find that regression analysis is less likely to identify B_3 as a significant predictor as the level of error correlation increases. When there is no error correlation, the model which includes B_3 and B_4 as significant predictors is most often produced (50 out of 100 trials), with the model containing B_4 as the only significant predictor being the next most likely model (38 out of 100 trials). As the error correlation increases, the B_4 model predominates (46 out of 100 trials at r=.90), while the model containing both B_3 and B_4 becomes less likely (40 out of 100 trials at r=.90). So, the number of times that the model including only the fourth predictor is produced increases, while the number of times that the model including both the third and fourth predictors is produced decreases, suggesting that as error correlation increases, regression analysis increasingly favors the model containing only the strongest predictor.

The pattern when N=100 is similar, the weaker predictors (B_2 and B_3) are less likely to be included in the model as the error correlation increases. When there is no error correlation, the model containing B_3 and B_4 predominates (produced in 58 of 100 trials), with the model containing only B_4 produced in 20 of 100 trials, and the model containing B_2, B_3, and B_4 produced in 13 out of 100 trials. At the highest level of error correlation, the model containing B_3 and B_4 is produced in only 46 of 100 trials, the

model containing only B_4 is produced in 38 of 100 trials, and the model containing B_2, B_3, and B_4 is produced in only 5 of 100 trials.

When N=200 (Table A-7), under conditions of no error correlation, the model including B_3 and B_4 again predominates, produced in 75 of 100 trials, the model containing B_2, B_3, and B_4 is chosen in 17 of 100 trials, and that containing only B_4 is chosen in only 3 of 100 trials. At the highest error correlation, the model containing B_3 and B_4 is produced in only 66 of 100 trials, the model containing B_2, B_3, and B_4 is produced in 11 of 100 trials, and that containing only B_4 is produced in 15 of trials.

Finally, when N=500, with no error correlation, the model containing only B_4 is not produced at all, the model containing B_3,B_4 is produced most often in 63 of 100 trials, and that containing B_2,B_3,B_4 (the "true" model) is the second most likely in 35 of 100 trials. As the error correlation increases, the model containing B_3,B_4 becomes more likely, produced in 78 of 100 trials, and that containing B_2,B_3,B_4 becomes less likely, produced in only 12 of 100 trials.

These results indicate that the weaker effect sizes are less likely to be detected as the level of observation correlation increases. At the smaller sample sizes (N=50 and 100), the analyses increasingly favored the model containing only the fourth predictor, and those models containing the second and third predictors became less likely. At the larger sample sizes (N=200 and 500), the model containing the third and fourth predictor was increasingly favored, while the model which included the second predictor became less likely to be produced.

These patterns suggest that the overall effect of error correlation in regression

analysis is to reduce the power of the analysis, increasing the risk of failing to detect significant predictors (i.e., increasing the risk of Type II error). How might we explain this phenomena? Inspection of the formulas for calculating standardized beta estimates and t-statistics suggests that this may be attributed to an overestimation of variance in the dependent variable.

$$\beta = \frac{Cov(x,y)}{Var(x)} \tag{36}$$

$$B = \frac{\sigma_x \beta}{\sigma_y} \tag{37}$$

$$t = \frac{(SS_{xx})^{.5}\beta}{\sigma_y} \tag{38}$$

When the variance of y is overestimated, the standardized beta weight will be underestimated. Additionally, when the variance of y is overestimated, the t-statistic is underestimated. In both cases, we experience a loss of analytic power, and an increase in the risk of committing Type II error.

The influence of error correlation on the variance of the dependent variable is confirmed by repeating the iterations as before and noting the means and standard deviations of the variance distributions for varying sample size and levels of error correlations. The results are provided in Table 1 below. These results clearly demonstrate that the mean and standard deviation of the variance distribution increases as the level of observation correlation increases, indicating that the variance is overestimated in the presence of observation correlation.

The above analyses are informative in understanding the effect of observation correlation

on analyses which are built upon sample variance (such as regression analysis and analysis of variance). However, many statistical techniques are built upon the principles of model fit, rather than hypothesis testing on individual parameters. It is important, therefore, to also examine the ways in which error correlation influences model fit. This can be accomplished by employing the iterative strategy outlined above, but instead of testing the parameter estimates using t-statistics, the entire model is evaluated using the

Table 1. Means and Standard Deviations of Beta Parameter Estimates for Varying Levels of Error Correlation and Sample Size

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
50	1.61 (.21)	1.63 (.24)	1.68 (.26)	1.71 (.28)	1.82 (.26)	1.89 (.32)	2.00 (.37)	2.06 (.40)	2.19 (.43)	2.44 (.45)
100	1.61 (.18)	1.66 (.16)	1.68 (.18)	1.75 (.20)	1.80 (.22)	1.86 (.23)	2.00 (.24)	2.10 (.26)	2.26 (.33)	2.49 (.37)
200	1.65 (.12)	1.63 (.10)	1.65 (.13)	1.74 (.13)	1.79 (.15)	1.86 (.18)	1.97 (.17)	2.13 (.21)	2.27 (.19)	2.35 (.23)
500	1.64 (.08)	1.64 (.08)	1.66 (.08)	1.71 (.09)	1.79 (.10)	1.86 (.10)	2.00 (.10)	2.12 (.12)	2.28 (.13)	2.46 (.15)

maximum log likelihood function (equation 33). The results of this analysis are provided in Table 2 below. These results confirm that model fit deteriorates (or lack of fit increases) with increasing error correlation.

All of these analyses indicate that we cannot analyze data containing observation interdependence without building in some type of mechanism for either accounting for the resulting error correlation or correcting it. The next section will test the alternative methods previously outlined for analyzing this type of data to determine those techniques which are most effective in producing results similar to those obtained when there is no observation interdependence.

Table 2. Means and Standard Deviations for Model Lack of Fit at Varying Sample Size and Level of Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
50	136.42 (3.2)	136.27 (3.45)	137.57 (5.49)	140.15 (5.95)	143.01 (7.75)	146.21 (8.79)	150.12 (8.80)	153.54 (11.08)	161.52 (10.18)	165.05 (12.01)
100	278.11 (3.56)	279.35 (4.38)	281.19 (5.95)	286.54 (8.24)	292.30 (10.78)	300.56 (11.77)	305.26 (12.66)	315.73 14.23)	327.19 (13.89)	334.59 (14.11)
200	562.37 (2.94)	563.66 (4.85)	568.88 (8.48)	579.66 (12.06)	591.24 (15.94)	604.15 (15.38)	623.18 (19.67)	641.45 (17.90)	662.50 (18.23)	683.21 (20.80)
500	1414 (2.99)	1418 (7.31)	1432 (11.41)	1459 (16.47)	1488 (24.50)	1526 (24.71)	1570 (27.53)	1608 (30.98)	1662 (34.13)	1708 (30.18)

Correcting or Accounting for Error Correlation

This section presents the results of using data transformation, structural equation modeling, and information theoretic criteria to analyze data while accounting for observation correlation.

Data Transformation and Autoregression Models

The discussion in Chapter 3 revealed that when the following transformation is performed on data with bivariate dependency between observations,

$$x_t = x_1 - r_{12}x_2$$

the dependency is eliminated and the data then follow a normal probability distribution. Thus, we should find that regression analyses carried out with the transformed data, at all levels of error correlation, will yield results similar to those obtained when there is no error correlation. Performing this transformation simply requires that we first calculate the level of correlation between the adjacent pairs of observations, and then transform the data as indicated above.

Tables A-9 through A-12 in Appendix IV (pp. 100-103) provide the results of the

regression analyses performed on the transformed data at varying sample sizes and levels of error correlation. The trends which were apparent in Tables A-5 through A-8 appear to have reversed following the data transformation. We found in the previous section that correlation between observations reduces the power of regression analysis. There appears to be a trend such that the variable transformation for observation correlation tends to overcorrect for the reduced power at error correlations higher than .50, so that there is an increased risk of Type I error (erroneously finding an effect to be significant) following data transformation. Since the reduced power was attributed to overestimated variance when observations are interdependent, it is possible that the data transformation causes the data variance to be underestimated. Table 3 provides the parameters of the variance distributions, with sample size and error correlation varying, after the data are transformed to account for the observation interdependence. The results confirm that the variable transformation does in fact cause the variance to be underestimated, which results in an increased risk of Type I error.

As noted in Chapter 3, the variable transformation is, in effect, simply an autoregressive model with the regression coefficient for the paired observation estimated *a priori* by the correlation between the paired observations. It is possible that a better model can be obtained by allowing this parameter to be estimated using least-squares in the autoregressive model. This is simply accomplished by leaving the outcome variable as is, and adding the paired observation vector as an additional predictor in the regression model. The results of these analyses are provided in Appendix V, in Tables A-13 through

Table 3. Means and Standard Deviations of Sample Variance Following Data Transformation at Varying Sample Size and Levels of Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
50	1.61 (.21)	1.53 (.21)	1.52 (.23)	1.44 (.22)	1.41 (.27)	1.29 (.22)	1.25 (.22)	1.19 (.23)	1.16 (.20)	1.11 (.19)
100	1.61 (.18)	1.56 (.15)	1.55 (.16)	1.48 (.19)	1.38 (.17)	1.34 (.16)	1.29 (.17)	1.17 (.16)	1.12 (.14)	1.12 (.14)
200	1.65 (.12)	1.60 (.11)	1.57 (.12)	1.49 (.13)	1.42 (.12)	1.33 (.11)	1.29 (.12)	1.19 (.12)	1.15 (.11)	1.14 (.10)
500	1.64 (.08)	1.60 (.07)	1.57 (.08)	1.50 (.08)	1.42 (.08)	1.35 (.09)	1.27 (.07)	1.20 (.07)	1.13 (.07)	1.11 (.07)

A-16 (pp. 105-108). The pattern remains the same as was apparent for the variable transformation. The autoregressive model also tends to overcorrect for the reduced power at higher levels of error correlation.

Structural Equation Models

Structural equation models allow the analyst to model the paired observations as latent constructs loading on a single, second-order latent construct. The outcome variable then is modeled as a function of the paired observations and the correlation between their error terms. The execution of this technique is more problematic than the others in this study. Structural equation modeling is computationally intensive, estimating a large number of parameters iteratively. While the analysis employing the other techniques could be carried out 100 analyses at a time in MATLAB, the structural equation technique has to be carried out one analysis at a time (this was accomplished using AMOS in conjunction with SPSS). As it was impractical to carry out 4,000 of these

analyses one at a time, these results are pared down considerably. The analyses were carried out for only one sample size (N=200), and only for error correlations of .00, .20, .40, .60, and .80, yielding 500 analyses. The results are presented in Table A-17 in Appendix VI (pg. 110).

We find that the distribution of models produced remains quite similar across all levels of error correlation, with the model containing the third and fourth predictors consistently predominating. Although this set of analyses is abbreviated, the results suggest that structural equation modeling appears to correct for observation correlation without increasing the risk of Type I error.

Information Theoretic Criteria

While there are a number of model evaluation criteria based on information theory, this study will test Akaike's (1973) AIC and Bozdogan's (1990) ICOMP. AIC evaluates models based on two components, the fit of the model and model parsimony. The best model is that which provides the best fit with the least number of predictors. The results for the AIC analyses are provided in Appendix VII in Tables A-18 through A-21 (pp. 112-115). AIC appears to effectively control for the presence of error correlation, providing similar results across all levels of error correlation for each of the four sample sizes.

ICOMP operates on principles similar to AIC. In addition to basing model evaluation on the model fit and the principle of parsimony, ICOMP assesses the degree of interdependence between parameter estimates. In this case, we are applying ICOMP to a vector autoregressive model, so that the degree of covariance between residual terms is

taken into account as models are evaluated.

The results of the ICOMP analyses are provided in Appendix VIII in Tables A-22 through A-25 (pp. 117-120). ICOMP appears to have no corrective effect for the loss of analytic power in the presence of error correlation. This may be attributed to the fact that, while the other techniques attempt to "filter out" or control for the error correlation, ICOMP penalizes for the presence of error correlation. In AIC, the maximum log likelihood equation filters out the error correlation in selecting the best model, by capturing the resultant model misspecification bias. While ICOMP also captures model misspecification through the maximum log likelihood function, it administers an additional penalty for the presence of error correlation. As the level of error correlation increases with the number of significant predictors, we find that ICOMP tends to favor the more conservative models.

ICOMP's performance may be improved by reformulating the lack of fit component. The residual covariance matrix which contributes to the complexity penalty is formulated as if we are assessing an autoregressive model. Each residual is paired with a residual with which it is expected to be correlated. Thus we may have better results by generating the parameter estimates by an autoregressive model, and using the residuals from this model to formulate ICOMP.

Tables A-26 through A-29 in Appendix IX provide the results from using ICOMP with an autoregressive model. At the smallest sample size (N=50) there may be a trend such that the most conservative model (containing only the fourth predictor) is less likely to be produced, while the larger models containing the second and third predictors become more likely as the level of error correlation increases. It appears that this

approach may have the tendency to overcorrect for the loss of analytic power as we observed when autoregression alone. This trend is less apparent when the sample size is 100. The trend is not monotone across all levels of error correlation, rather the frequency of choosing a particular model seems to fluctuate. For the sample of moderate size (n=200) the results are quite similar from levels of error correlation from .10 to .90. Finally, at a sample size of 500 there is no definite trend, but the figures seem to fluctuate widely by level of error correlation.

This reformulation of ICOMP exhibits improved performance in eliminating the influence of observation correlation. Although there may be some tendency to overcorrect with small samples, using ICOMP with moderate or large samples should provide good results.

Summary

Structural equation modeling and Akaike's Information Criteria are most effective in recovering the analytic power which is lost in the presence of obervation interdependence. Transformation of the outcome variable and autoregression overcorrect for the loss of power, increasing the likelihood of Type I error. The loss of analytic power arising from the presence of observation correlation remains apparent when using Informational Complexity Criteria for model evaluation. However, when combining ICOMP with an autoregression model, this approach provides much better results, although there may still be a tendency to overcorrect for the loss of analytic power at smaller sample sizes.

Replication of Harris and Marmer (1996)

There are two goals to be addressed in this section. The first is to examine any changes in analytic results when observation interdependence is taken into account. The second is to examine any change in analytic results when different sampling strategies are employed.

Description of the Data

This part of the analysis begins by reconstructing the data set and the model variables as set out in Harris and Marmer (1996) as closely as possible. As it is not unusual for data analysts to make minor adjustments to the data (such as deleting cases with missing values or substituting for missing values) without fully reporting such adjustments in the published manuscript, it is reasonable to expect that the Harris and Marmer study will not be exactly reproduced. This reconstruction does however, come quite close to that reported by Harris and Marmer (1996).

In the original study, the sample was restricted to include only those children who had been living with two parents during all three waves of data collection, resulting in a total sample size of 748 children. Carrying out the same screening process in the current study resulted in a total sample size of 746. Harris and Marmer carry out their regression analyses for five categories of poverty status. One classification divided the sample into those who were never poor (income above the poverty line in Wave 1 and Wave 2), those who were temporarily poor (income below the poverty line in either Wave 1 or Wave 2), and those who were persistently poor (income below the poverty line in both Wave 1 and Wave2). A second classification divided the sample into those who had ever received

welfare assistance (either AFDC or food stamps in either Wave 1 or Wave 2), and those who had never received welfare assistance. Their categorization resulted in 554 families who were never poor, 124 families who had been temporarily poor, 70 who were persistently poor, 658 families who had never received welfare, and 77 who had received some welfare assistance. The totals for income history and for history of welfare assistance do not, however, add to their total sample size, and the missing cases are not explained in their report. In the current study, we have 564 children who were never poor, 109 who were temporarily poor, 73 who were persistently poor, 628 who had never received welfare assistance, and 118 who had received some welfare assistance. Again, while not arriving at the exact delineations which Harris and Marmer employed, the numbers in this study are close to the original study, and should produce similar results.

Harris and Marmer created four predictor variables from the NSC data set: father's emotional involvement, father's behavioral involvement, mother's emotional involvement, and mother's behavioral involvement. The items used to construct this scale are clearly identified in the published manuscript. While the means and standard deviations for these variables are not reported, they did report the Cronbach's alphas for each scale, allowing some comparison between their measures and those used in this study. Harris and Marmer reported alphas of .71 for father's emotional involvement, .56 for father's behavioral involvement, .59 for mother's emotional involvement, and .53 for mother's behavioral involvement. The same variables in the current study produced alphas of .69 for father's emotional involvement, .57 for mother's emotional involvement, .57 for father's behavioral involvement, and .51 for mother's behavioral

involvement. These figures are remarkably close to those obtained by Harris and Marmer.

Finally, Harris and Marmer use four outcome variables as indicators of child wellbeing: educational and economic attainment, delinquency, depression, and teen pregnancy. Teen pregnancy could only be constructed as a dichotomous outcome variable, and therefore was not suitable for this study. While similar techniques could probably be developed for logistic regression, this is certainly beyond the scope of this study. The authors also chose to construct their depression variable as a dichotomous variable, separating out those at the very highest levels of depression. For the current study, depression remains as a continuous variable, therefore some of the results on this outcome in the current study may differ from those obtained by Harris and Marmer. Its inclusion in the analysis should prove to be instructive in any case.

The educational and economic attainment scale is complex, with cases scored according to whether or not they had attended or were attending college, whether or not they had graduated from high school, whether or not they were currently in school or in steady employment, and whether or not they had ever failed a grade or dropped out of school. This variable was quite difficult to reconstruct. The mean score on this measure (with a range of 1 to 5) in the original study was 2.08, and it was 3.25 in the current study (with a standard deviation of 1.32). It appears that a disproportionate number of cases were coded as having higher educational and economic attainment in the current study compared to the original study, and therefore the regression results for this outcome variable may differ from those obtained by Harris and Marmer.

The items include in the delinquency scale were not clearly specified by Harris and Marmer, and therefore all items which appeared to be relevant were included in the scale used in the current study. They report that 33.5% of their sample reported only one delinquent act, and 10% reported two or more delinquent acts. In the current study, we have 13.1% reporting only one delinquent act and 13.7% reporting two or more delinquent acts. Harris and Marmer have somehow captured a large proportion of individuals reporting only one delinquent act, who were not picked up in the current study. Our results therefore cannot be expected to correspond exactly to those obtained in the original study.

As was true for the delinquency scale, Harris and Marmer did not report the exact items used to construct their depression scale. Therefore, the current study employs all apparently relevant items in the scale. They report that 21% of their sample scored more than one-half of a standard deviation above the scale mean (although the mean and standard deviation are not reported). In the current study, 33% of the sample fall above one-half of a standard deviation above the mean (mean = 44.02, standard deviation = 6.44).

In the data set for the current study, 48% of the children consist of sibling pairs and the remaining 52% were single measures. The observation correlations on the outcome variables among the sibling pairs were .884 for educational and economic attainment, .155 for delinquency, and only .054 for depression. The observation correlations for parental involvement were .403 for paternal emotional involvement, .313 for paternal behavioral involvement, .296 for maternal emotional involvement, and .382

for maternal behavioral involvement.

Overall, the data set reconstructed for our current analysis should provide results which are quite to close those obtained by Harris and Marmer. Certainly, the current data will suit our purposes, as we are simply seeking to create some "baseline" results for comparison as we apply techniques to correct for observation interdependence and as we apply different sampling strategies.

Accounting for Observation Interdependence

This analysis began by performing a regression of three separate child outcome variables (educational and economic attainment, delinquency, and depression) on four parental involvement variables (father's and mother's emotional and behavioral involvement) within five categories of poverty status (results provided in Tables A-31 through A-34 in Appendix X, pp. 122-126). Harris and Marmer anticipated that the negative effect of poverty on child wellbeing would be buffered by parental involvement, suggesting that we would find stronger effects for parental involvement on child wellbeing within the categories indicating impoverishment.

Harris and Marmer found 9 significant effects - four for the effect of maternal involvement and five for the effect of paternal involvement on child well being. Among the impoverished subsample, they found two significant effects for maternal involvement and only one significant effect for paternal involvement. They found that among those children who had been persistently poor and had received welfare, those with mothers who were behaviorally involved exhibited higher educational and economic attainment, and those whose fathers were emotionally involved exhibited lower levels of delinquent

behavior.

The current analysis produced eight significant effects - seven significant effects for maternal involvement and only one significant effect for paternal involvement. Six of the significant effects are apparent among the most impoverished subsample, with one attributed to paternal involvement and the remainder for maternal involvement. These results are, in fact, quite close to those obtained by Harris and Marmer. We find that, without correcting for observation interdependence, among those children who were persistently poor or who had received welfare assistance, those who had emotionally involved mothers exhibited higher educational and economic attainment, those with behaviorally involved mothers exhibited less depression and delinquency, and those with emotionally involved fathers exhibited less depression.

The data were then reanalyzed using structural equation modeling and AIC to determine whether we obtain different results when we correct for the presence of observation interdependence.

The results indicate that structural equation modeling and AIC consistently produce additional significant effects compared to when no correction for observation interdependence is employed. Together these techniques produced 23 additional significant effects, a total of 32 significant effects. Specifically, we find 8 additional effects for maternal involvement and 15 additional effects for paternal involvement, yielding a very different picture from that obtained with no correction for observation interdependence. Among the most impoverished subsamples, these techniques produced 7 additional effects - two effects for maternal involvement and five for paternal

involvement. These results confirm those obtained in the analysis of simulated data; it does appear that we gain additional analytic power by correcting for observation interdependence.

After correcting for observation interdependence, we can conclude that, among those children who were persistently poor and who had received welfare, in addition to the effects noted above, those with behaviorally involved mothers exhibited higher levels of education and economic attainment and lower depression, those with emotionally involved fathers exhibited higher education and economic attainment, and those with behaviorally involved fathers exhibited higher levels of educational and economic attainment, lower delinquency, and lower rates of depression.

Overall, these findings suggest that both mothers and fathers have a significant influence on child wellbeing, and that their role may be particularly important among economically distressed children. While the fundamental question which Harris and Marmer sought to address was whether parental influence on child outcomes differed across poverty levels, this interaction was never actually tested directly. Therefore, one last analysis was conducted, testing for the influence of paternal involvement (collapsing behavioral and emotional involvement), maternal involvement, poverty status, and for an interaction between poverty status and paternal involvement, and between poverty status and maternal involvement on child outcomes. The models with all possible combinations of predictors were evaluated using AIC. Child delinquency was not predicted by any of the predictors (the model containing only the constant was the best model). Child educational and economic attainment was predicted only by poverty status. Only child depression was influenced by parental involvement, and the interaction terms were significant for both paternal and maternal involvement. These terms indicated that

mothers had an increasingly positive effect on depression as poverty increased (B=.2150). That is, impoverished children tended to be more depressed with more involved mothers. On the other hand, fathers exhibited an increasingly negative effect on depression as poverty increased (B=-.4173), indicating that impoverished children were less depressed with more involved fathers.

Thus, we find that the influence of parental involvement varies by poverty status only for child depression, and that the interaction terms work in opposite directions for mother and father involvement. More importantly, all of these analyses indicated that correcting for observation interdependence allowed a number of significant effects to come through, providing much richer results than were obtained with no correction.

Testing Sampling Strategies

The final part of the analysis involved constructing four samples and performing the same regression analyses for the purpose of comparison (results provided in Tables A-35 through A-39 in Appendix XI, pp. 128-132). The first two columns of each table present the results employing measures for multiple children from each family (N=746), with the observation interdependence corrected by Structural Equation Modeling and AIC. The third column of each table presents the results of the same analyses conducted on a sample using only the youngest child when two children were available (N=568). The fourth column employs only the oldest child when two or more were available, and the fifth sample includes one child chosen randomly when two were available.

The results indicate that nearly all of the significant effects are lost in at least one of the three restricted subsamples. 18 significant effects are lost completely when the sample is restricted to measures on one child per family - 10 paternal involvement effects and 8 maternal involvement effects. The lost effects are evenly spread among the

categories of poverty status and among outcome variables. There were 11 additional significant effects lost in at least one of the restricted subsamples. We find that 6 significant effects are lost when the sample is restricted to the youngest child, 4 effects are lost when the sample is restricted to the oldest child, and 10 significant effects are lost when one target child is randomly chosen.

In summary, these analyses indicate that a significant amount of information is lost when the sample is restricted to only one child per family. Richer and more valid results are obtained when measures are taken from multiple members of each family.

CHAPTER 5

CONCLUSIONS

This study was constructed to address the need for including measures from multiple members of the family in studying family phenomena. Although this point has been made on other occasions in the literature, this sampling practice continues to be avoided, most likely due to the fact that we have not yet developed analytic techniques appropriate for data with nonindependent observations. Many scholars who have included multiple family members in their samples (usually large national data sets), have typically ignored the observation interdependence in carrying out their analyses. Therefore, this study had three goals: 1) To demonstrate the need for measures from multiple family members; 2) To demonstrate the influence of observation interdependence on analytic results; and 3) To test several alternative analytic techniques for analyzing data with nonindependent observations.

Determining the proper order for addressing these issues is difficult, as the proper treatment of each issue relies to some extent on the resolution of the others. We cannot compare the results of analyzing measures from single versus multiple family members, without first developing the techniques which will allow us to do so. We cannot test alternative techniques for analyzing data with nonindependent observations, without first determining whether such techniques are necessary and under what conditions, and being able to explain why alternative techniques are necessary. Finally, we have no reason to entertain notions about the influence of observation interdependence on analytic results, if

we have no need to study data with this characteristic.

For the purposes of this discussion, we will begin by assuming that measures from multiple families members are necessary and desirable, and proceed to discuss the analytic difficulties that arise from this sampling strategy, and then examine ways to deal with these analytic difficulties. We will end by returning to the issue of whether our research is indeed improved by including measures from multiple family members.

The Influence of Observation Interdependence on Analytic Results

Observation interdependence creates analytic difficulties because its presence violates one of the fundamental conditions of the Central Limit Theorem, which is the basis of most of our analytic techniques. The Central Limit Theorem states that when a sample is drawn such that each observation is independent of all others, the standardized form of that variable will follow an asymptotic standard normal distribution. This theorem allows us to use z-, t-, F-, and χ^2-statistics to assess our parameter estimates in determining the nature of the relationships between variables.

Analyzing data which include measures from multiple family members without taking observation interdependence into account produces questionable results. It may be that regression analysis, analysis of variance, contingency analysis, and structural equation analyis are robust to some extent, so that lower levels of observation interdependence do not affect our outcomes. However, we cannot know this for certain, and certainly cannot know at what point our methods are no longer robust, without directly examining the effect that this data characteristic has on analytic results under varying conditions.

The use of simulated data facilitates this type of analysis. With this technique, we can create a large number of data sets of varying size and with varying predetermined characteristics. We can then alter each sample in some way and determine the analytic effect of the modification. In this study, 4,000 samples were "drawn" from a population with predetermined characteristics. The population had a standard normal distribution, and the outcome variable was created as a function of the standardized predictor variables drawn from this population, so that the relative magnitude of the relationships between the predictors and the outcome variable would be maintained between samples. The data were designed so that the outcome variable would have no relationship with the first variable, a weak relationship with the second, a moderate relationship with the third, and a strong relationship with the fourth predictor. Random error was then added to the model, with progressively increasing correlation between the error terms in order to induce observation interdependence in the outcome variable.

It was determined, both mathematically and intuitively, that one effect of observation interdependence would be to reduce the variance in the outcome variable. Under the conditional normal probability distribution the variance of the outcome variable is

$$\sigma^2(1-\rho^2).$$

Accounting for observation interdependence then effectively reduces the sample variance by a factor of $(1-r^2)$. Failing to account for observation interdependence therefore results in an overestimation of the variance in the outcome variable. Overestimating the variance of the outcome variable should also affect the standardized beta parameter estimates.

Beta weights are standardized by dividing the raw parameter estimates by the standard deviation of the outcome variable. Therefore, an overestimation of the outcome variance should result in an underestimation of the standardized beta parameter estimates. Finally, an overestimation of the outcome variance would influence the t-statistic in assessing the parameter estimates. The t-statistic is calculated by dividing the parameter estimate by its standard error. When the outcome variance is overestimated, the standard error of the parameter estimate is also overestimated, resulting in the t-statistic being underestimated. The effect of this result is a loss in analytic power and an increase in the risk of committing Type II error (failing to reject a false null hypothesis).

A series of analyses were conducted to test these theoretical expectations. The influence of observation interdependence on analytic results was determined by monitoring the variance of the outcome variables and the mean parameter estimates in the simulated samples under increasing levels of error correlation. The influence of increasing levels of observation interdependence on model fit was also examined by monitoring the values of the maximum log likelihood equation under increasing levels of error correlation. It was anticipated that model fit should deteriorate with increasing levels of error correlation, as the distribution would increasingly deviate from the standard normal probability distribution. Finally, the influence of observation interdependence on analytic power was determined by examining the number of times in which the correct model was produced under increasing levels of error correlation.

The analyses confirmed all four of these expectations. The mean standardized beta parameter estimates were reduced by 13-22%, and the effect did not tend to vary by

sample size. This result suggests that, in failing to account for observation interdependence, we are producing beta weights which are less likely to be determined to be significant, thus we are increasing our risk of committing Type II error.

The tests for our ability to detect the correct model at increasing levels of error correlation confirmed a loss in analytic power. We found that our ability to detect the influence of the second and third predictor variables, which had a weak and moderate relationship with the outcome variable respectively, was reduced as the error correlation increased.

It was also confirmed that these two results were likely due to an overestimation of the variance in the outcome variable. This analysis revealed that the estimated outcome variance increased 42%-55% as the error correlation increased. With regards to model fit, it was determined that model fit deteriorated, or that lack of fit increased, by about 21% for all sample sizes.

The most important conclusion from these analyses is that we can expect to experience a significant loss in analytic power if we fail to account for observation interdependence when using measures from multiple family members. The effects which tend to be weak to moderate, but are significant, will be lost if some effort is not made to correct for the correlations between the observations. The loss of power became most apparent when the error correlation reached about .30 with a sample size of 50 and 100, but did not become really apparent until the error correlation reached .50 or more with the larger samples of 200 and 500. This conclusion suggests that the influence of observation interdependence on analytic results does depend on both sample size and the level of

correlation between the observations. Generally, larger sample sizes may render the analyses more robust, but some correction should be made, regardless of sample size, when the observation correlations are .50 or higher.

Analytic Techniques for Data with Nonindependent Observations

The first goal of this study was to establish the impact that observation interdependence has on analytic results. We found that the presence of observation interdependence produced an overestimation of the sample variance for the outcome variable, which resulted in a loss of analytic power.

The second goal of this study was to develop and test alternative methods for analyzing data under these conditions. The first method was developed by this author, from basic principals of mathematical statistics. The presence of observation interdependence renders the probability distribution conditional. The probability function for the conditional distribution was derived by dividing the bivariate normal probability distribution by the univariate normal probability distribution for the paired dependent observation vector. The resulting formula suggests that by transforming the data so that

$$x_t = x_1 - (rx_2),$$

the data should now follow a normal probability distribution with independent observations.

The method was tested by creating a series of samples, using the strategy previously described, with 100 samples each containing 50, 100, 200, and 500 observations, and with observation correlation ranging from .00 to .90, for a total of 4,000 samples. By monitoring the number of times that the correct model was chosen, we

found that when the observation correlation reached a level of .60 or higher, the analyses tended to have too much analytic power, so that the risk of committing Type I error (rejecting a true null hypothesis) was increased. For the smaller sample sizes (N=50 or 100), models which included the third predictor (that which had a moderate influence on the outcome) became much more likely at higher levels of error correlation. For the larger sample sizes (N=200 or 500), models which included the second predictor (that which had a weak influence on the outcome) became much more likely at higher levels of error correlation.

As we had found in the previous section that we could attribute the loss in analytic power to overestimated outcome variance under the condition of observation interdependence, it was proposed that the excessive analytic power which resulted from the data transformation may be attributed to an underestimation of the outcome variance. This result was confirmed by a progressive decrease in the outcome variance as the error correlation increased at all sample sizes.

While it is not clear exactly why this pattern occurs, it might be attributed to bias which is introduced into the analysis through the estimation of the correlation term for the paired observations. It was theoretically determined that, in the presence of observation interdependence, the sample variance is overestimated, requiring a corrective factor of $(1-\rho^2)$. As the value of the population correlation between the paired observations is not determinable, we substitute the sample correlation. This estimation introduces error such that the true correlation may be overestimated, producing an underestimated corrective factor and underestimated outcome variance.

Closer examination of the data transformation revealed that the corrective factor could be estimated through least squares using an autoregressive model with the paired observations as an additional predictor variable. This technique was tested in the same manner as was previously described, and the results were the same as were obtained through the data transformation. For the smaller sample sizes, at higher levels of error correlation, models including the third predictor variable became more likely. For the larger sample sizes, at higher levels of error correlation, models including the the second predictor variable became more likely. This result was surprising, as it was expected that the error introduced by estimating the observation correlation might be corrected by using least squares to estimate this term. This was not the case, as an excess in analytic power was as apparent using autoregression as when using the data transformation. It is possible that the least squares method introduces estimation error which has the same effect as the error resulting from the estimated correlation term.

The second alternative method employed a structural equation model, where the paired observations were loaded on a single outcome latent construct. The correlation between the error terms for the paired observations was then included in the model for estimation, and taken into account when estimating the beta parameters, or the relationship between the latent constructs. This technique uses iterative strategies for estimating the model parameters, rather than least squares or maximum likelihood estimates, and has the additional advantage of modeling the measurement error, presumably producing more accurate beta estimates and better overall model fit. Therefore, we would expect that this technique would prove to be superior to both data

transformation and autoregression in accounting for the influence of observation interdependence.

While it was impractical to conduct 4,000 iterations of analyses using this method, the pattern which emerged from only 500 iterations seems clear. At a moderate sample size (N=200), the correct balance between the best models produced at each iteration was preserved at error correlations of .00, .20, .40, .60, and .80. There appears to be no reduction or excess in analytic power when using this method to account for observation interdependence.

The last two methods were based on information theory. Akaike's Information Criteria (AIC) includes one component which measures lack of model fit, and another which indicates a lack of parsimony. The lack of model fit is determined by multiplying the maximum log likelihood function by a factor of -2. The lack of parsimony is determined by multiplying the number of factors in the model by 2. These components are then summed to produce the criterion, and the best model is selected when the criterion is minimized. As the presence of observation interdependence reduces fundamentally to a problem with model misspecification, it was anticipated that the bias arising from this misspecification would be captured through the maximum log likelihood function. This would render AIC an effective tool in selecting the best predictive model while taking the effect of observation interdependence into account.

AIC proved to be highly effective for the purpose of selecting the best model in the presence of observation interdependence. The balance between selected models was preserved relatively well across all levels of error correlation and at all sample sizes.

However, there did appear to be a significant amount of random fluctuation in selected models as we progressed from one level of error correlation to another. While this does not diminish the effectiveness of AIC in accounting for observation interdependence, it does suggest that this method may be generally unstable, with the results being somewhat "sample dependent."

In addition to AIC, Bozdogan's Informational Complexity (ICOMP) criterion was tested as the final alternative. While accounting for model lack of fit and lack of parsimony, ICOMP provides a significant additional benefit in accounting for dependence between and among the parameter estimates. This condition is most often observed when the data contain a high level of multicollinearity. It was anticipated that ICOMP may also be useful in providing an additional means of accounting for dependence among residuals or error correlation.

Contrary to expectations, ICOMP did not prove to be effective in correcting for the loss of analytic power arising from observation interdependence. For all sample sizes, as the level of error correlation increased, ICOMP tended to increasingly favor the model containing only the fourth predictor. It stands to reason that the level of error correlation would increase with the addition of predictive variables. In the absence of a predictive model, the errors would be random, and we would expect little correlation between the observations. However, as our predictive model improves, we should find that the error correlation will increase. This would result in ICOMP favoring the smaller models, if the improvement in fit does not offset the penalty created by increasing error correlation with additional predictive variables. In fact, it could be argued that, rather than failing to

correct for a loss in analytic power, ICOMP provides a more accurate measure by maintaining a more conservative approach in the presence of "ill-conditioned" data.

Overall, these analyses indicate that structural equation modeling and AIC are most effective in correcting for the loss of analytic power which occurs in the presence of observation interdependence, without overcorrecting and thus increasing the risk of Type I error.

Using Measures from Multiple Family Members

The fundamental argument in this dissertation is that our study of the family will be improved by incorporating measures from multiple family members. While this notion is conceptually appealing, our lack of techniques to correct for observation interdependence has rendered family scholars unable to test the proposition. Having established that observation interdependence generates a loss in analytic power, and that structural equation modeling and AIC effectively counteract this reduction in power, we are now able to directly test whether we can obtain more valid and more accurate results by using measures from multiple family members.

Retesting Analytic Alternatives

Before testing different sampling strategies, we retested four of the five alternative analytic strategies with real data from the National Survey of Children. A model employed by Harris and Marmer (1996) was reproduced, examining whether parenting factors might buffer the negative influence of poverty status on child outcomes. It was expected that additional significant effects would be apparent when the observation interdependence was taken into account analytically using structural equation modeling

and AIC.

The results confirmed that both structural equation modeling and AIC allowed additional significant relationships to become apparent. Among those families who were never poor, the only significant effect (using no corrective methods) was the influence of the mother's emotional involvement on the child delinquency. Structural equation modeling and AIC indicated that the mother's behavioral involvement also influenced child educational and economic attainment, and that both father's and mother's involvement, behaviorally and emotionally, were associated with lower levels of depression. The results were the same for the families who had never received welfare, and additionally indicated that both mother's and father's behavioral involvement were associated with increased educational and economic attainment.

Among those families who had experienced temporary poverty, there were no significant relationships between parenting factors and child outcomes without corrective methods. Structural equation modeling and AIC indicated that children achieved more educationally and economically when fathers were more involved behaviorally and mothers were more emotionally involved. Children were also less likely to exhibit delinquent behaviors when father's were behaviorally involved, and they were less depressed when both mothers and fathers were involved behaviorally and when mothers were emotionally involved.

For families who were persistently poor, only three relationships were significant between parenting factors and child outcomes. Mother's emotional involvement was associated with educational and economic attainment, mother's behavioral involvement

was significantly related to child delinquency, and father's emotional involvement was associated with child depression. Structural equation modeling and AIC indicated that children also experienced higher educational and economic attainment when fathers were emotionally involved and mothers were behaviorally involved. In addition, these techniques indicated that child depression was influenced by the mother's emotional and behavioral involvement.

Among those families who had received welfare, only three relationships were again significant without corrective analytic methods: children had higher educational and economic attainment when mothers were more emotionally involved, and they were less depressed when mothers were more involved both emotionally and behaviorally. Structural equation modeling and AIC indicated that child educational and economic attainment were also influenced by the father's involvement, both emotionally and behaviorally. It was also found that children exhibited fewer delinquent behaviors when fathers were emotionally involved.

There were no apparent patterns in which effects proved to be significant with the corrective methods. Both mother and father effects came through, and this was true for all poverty statuses and for all child outcomes. The only notable pattern was that the father's influence over child outcomes was notably absent without correcting for observation interdependence. This was no longer the case when observation interdependence was taken into account.

Our conclusion from the simulated data analyses is confirmed in these analyses. Important effects are lost through the reduction in analytic power which occurs in the

presence of observation interdependence. While it may be important to incorporate measures from multiple family members, any benefits will be lost if appropriate methods are not employed to counteract the resulting loss in power.

Testing Sampling Strategies

Having confirmed that our selected methods were able to counteract the reduction in analytic power which occurs with interdependent observations, we were ready to test whether our results would be improved by incorporating measures from multiple family members. This was accomplished by comparing the results obtained when up to two children per family were included in the sample, using appropriate corrective methods, to those obtained when only child per family was included. The target child was chosen first by birth order, the youngest and then the oldest, and then the choice was made again randomly.

Using measures from multiple children per family and correcting for observation interdependence, we found that among those families who were never poor, children had higher educational and economic attainment when mothers were behaviorally involved, they were less delinquent when mothers were emotionally involved, and they were less depressed when both parents were emotionally involved. The mother's influence on the child's educational and economic attainment was lost for the oldest child, her effect on child depression was lost for the youngest, and the father's effect on depression was lost in all three sampling strategies.

Among families who had never received welfare, child educational and economic attainment was influenced by the father's behavioral involvement and the mother's

involvement on both dimensions. Child delinquency was influenced by the mother's emotional involvement, and child depression was influenced by both father and mother involvement on both dimensions. The parental influence on child educational and economic attainment was lost completely with all three strategies for choosing one target child. The effects for the mother's and father's behavioral involvement on child depression were also lost in all three sampling strategies. The influence of the parent's emotional involvement on depression appears to depend on birth order. The effect of the mother's emotional involvement on child depression was lost when the youngest child was chosen for the sample, but the effect of the father's emotional involvement on child depression was only apparent for the youngest.

Among the families who were temporarily poor, child education and economic attainment were influenced by father involvement on both dimensions and by the mother's emotional involvement. Child delinquency was influenced by the mother's emotional involvement. The mother's involvement on both dimensions and the father's behavioral involvement were associated with child depression. The parental influence on child educational and economic attainment was apparent only when the target child was chosen randomly, while the influence of the mother's involvement on child depression was lost completely using all three sampling strategies. The relationship between the mother's emotional involvement and child delinquency was apparent only for the oldest child, while the influence of the father's behavioral involvement on child depression was apparent only for the youngest.

For persistently poor families, children achieved more educationally and

economically when fathers were more emotionally involved and when mothers were more behaviorally involved. The mother's behavioral involvement was also associated with fewer child delinquent behaviors. Child depression was influenced by the father's emotional involvement and by the mother's involvement on both dimensions. The influence of the father's emotional involvement on child educational and economic attainment, as well as the influence of all parenting variables on child depression were lost with all three sampling strategies. The influence of the mother's behavioral involvement on child educational and economic attainment was retained only when the child was chosen randomly. The influence of the mother's behavioral involvement on child delinquency was not apparent for the youngest child.

For families who had received welfare, child educational and economic attainment was influenced by father involvement on both dimensions and by the mother's emotional involvement. Child delinquency was influenced by the father's emotional involvement, and child depression was affected by the mother's involvement on both dimensions. The father's influence on child educational and economic attainment was lost for all three sampling strategies, while his influence on child delinquency was apparent only for the oldest child. The mother's influence on child depression was apparent only for the youngest child.

Two general patterns emerged from this analysis. When a birth order effect was apparent, the parental influence on delinquent behavior tended to be apparent only for the oldest child, while the parental influence on depression was apparent only for the youngest. It also appears that, when there is a birth order effect, fathers tend to retain

influence over the younger child, while mothers retain influence over the older. In any case, it seems very clear that important relationships are lost when only one child per family is sampled.

We can summarize the effects of using measures from multiple children per family by looking back at how well the analysis answered Harris and Marmer's original research question comparing analyses with and without multiple children. In the original study, Harris and Marmer hypothesized that parental involvement would buffer the negative impact of poverty on child well being, but they never directly tested this hypothesis. The most direct approach would have been to simply form interaction terms between poverty status and mother or father involvement and run a regression model for each outcome. Harris and Marmer chose to run these regression models separately for subsamples characterized by their poverty status, and to compare the results in order to deduce whether parental influence on child outcomes appeared to vary by poverty status. This is not only difficult to accomplish procedurally (it is not easy to detect subtle patterns in such a large number of results), but it is not correct. Even if a relationship is significant in one group, and not in another, it may be attributed to different sample sizes or to different levels of variance, rather than because the relationship actually does exist in one population and not in another.

A very simple regression analysis, with the models evaluated using AIC, indicated that parental influence on child outcomes varies by poverty status only for child depression, and that this relationship exists regardless of the sampling strategy. Only poverty predicted the child's educational and economic attainment well, and neither

poverty nor parenting factors predicted delinquency well. For child depression, the parental involvement by poverty interaction terms indicate that mothers had an increasingly positive effect on child depression as poverty increased, while fathers had an increasingly negative effect on child depression as poverty increased. In other words, children from poor families with very involved mothers tended to be more depressed, while the same children with very involved fathers tended to be less depressed. We might conclude from these results that having an involved mother increases depression for impoverished children, but that is not necessarily the case. This association could plausibly work in the reverse direction, so that mothers tend to be more involved with very depressed children. It is, however, of interest that in terms of an ameliorative effect, it appears that fathers are more effective in buffering depression among impoverished children than mothers are.

While this is an interesting result, it is unfortunate (for this study) that the effect did not vary when multiple versus single children per family were used. However, the result remains useful, and worth noting, because it cannot be reasonably argued that any family study which fails to assess multiple family members is invalid. It simply depends on the research question. There were a number of differences which came through when we examined specific parenting behaviors for specific income groups for different target children. With this approach, we found that the ways in which poverty affects children may vary by birth order and that the mothers and fathers may influence their children differentially by birth order. However, these subtleties were lost when we asked a very simple analytic question: Does a mother's or father's involvement influence children

differentially depending on their poverty status? The answer is yes; the effect of the involvement of both mothers and fathers on child depression intensifies for poorer children, and this tends to be true regardless of the sampling strategy. In other words, there are some phenomena which are "universal" within the family, they exist no matter which family member you look at. However, we usually cannot know that going into a research project (although we might anticipate and test it), and so it makes sense to gather as much information as is available.

Summary and Future Directions for Research

This study began with three basic questions. The first question sought to identify whether observation interdependence influenced analytic outcomes in statistical analysis, and if so to describe the nature of its influence. It was determined that the presence of observation interdependence in sample data creates a loss of analytic power. The effect appears to be dependent on both level of observation correlation and sample size, so that the loss of analytic power became most apparent when the error correlation reached .30 for smaller sample sizes, and when the error correlation reached .50 for the larger sample sizes.

The second question was concerned with developing and testing alternative techniques for analyzing data with nonindependent observations. Three techniques were introduced, with two additional techniques which were extensions of the others. Of the five techniques, structural equation modeling and AIC appeared to be most effective in correcting for the loss of analytic power. In the simulated data analysis, the data transformation and autoregression analysis appeared to overcorrect for the loss of power,

and increased the risk of Type I error. Finally, ICOMP tended to be more conservative than the other four, favoring models containing only the strongest predictor across all sample sizes.

The last question addressed the substantive implications of using multiple measures, as opposed to selecting a single observation per family, by examining variation in the results obtained with differing sampling strategies. The number of significant effects tripled with the use of structural equation modeling and AIC, confirming that analytic power is increased when these methods are employed to correct for the presence of observation interdependence. Those effects which became significant were evenly distributed between mother and father effects, among poverty status groups, and among child outcomes. That is, the increased power was evident across all tested effects.

It is important to note that while the analysis which contained no corrective factor produced only one significant effect for fathers. However, once observation interdependence was taken into account, it was apparent that both mothers and fathers played important roles in the lives of their children at all income levels. This result is especially important as Harris and Marmer had concluded that, "there are few buffering effects of fathers in poor families" and that "When we ask whether poor parents make a difference in their children's lives, our data suggests that mothers are more instrumental than fathers." This is a troubling conclusion, given that it is in error, and that it has the potential to significantly impact on policy formation in the distribution of government assistance and support services.

Testing different sampling strategies allowed us to see that the use of measures

from multiple family members also revealed some subtle patterns. Specfically, parental factors were more effective in ameliorating depression in the youngest child, and in ameliorating the occurrence of delinquent behavior in the oldest child. It also appeared that fathers tended to have influence on more outcomes for the youngest child, while mothers appeared to be more influential for the oldest child. These patterns would not have been discernable if measures had been restricted to a single child per family.

Finally, it was determined that the answer to the fundamental question posed in the Harris and Marmer study was the same regardless of sampling strategy. While this result is somewhat disappointing, it is realistic in that, while taking measures from multiple family members is likely to be beneficial in many cases, it will not always be so. There will be some research questions for which "cross-section" sampling is quite appropriate. In most cases, however, it cannot be assumed that taking measures from a single individual per family is adequate, and it is advised that researchers obtain as much information as is available, and make every effort to obtain as much information from a family as possible.

While the simulated data analysis provided important results, which could not practically be obtained with real data, further work should be done in testing these principles with real data. While our theoretical expectations may hold in a general sense, there are likely to be a myriad of special circumstances which will enrich our understanding of the need for measures from multiple members of the family. The most important of these is likely to be the nature of the research question. Some phenomena will be more likely to vary among family members than others, but we usually cannot

know this without testing it.

Future research on the influence of family factors on child outcomes would also likely benefit by measuring three or more children from each family when available. Generally, we play out our family roles within the context of the entire family, rather than expressing the sum total of our role within a single dyad. By the same token, it is not reasonable to closely examine parental influences on two children, when the third may be an interesting exception.

In addition, it would be important to avoid restrictive age ranges in selecting target children. While the National Survey of Children data was ideal for this study in many respects, it should be noted that the included siblings were a maximum of four years apart. We are likely to find greater variation among family members when we allow a broad range of ages to be included in our samples.

Finally, while large national studies provide numerous advantages, they tend to be limited in terms of the brevity of their measures. Smaller studies with richer measures may provide better insight into the importance of including multiple family members.

This study is concluded with two hopes. One is the hope that taking advantage of all of the information available to us from a given family will become a norm, as opposed to fashioning studies which target very narrow study populations inappropriately. The second is that, within the field of Family Studies, we will continue to develop new techniques, and apply established techniques from other fields, in an effort to effectively study "real world" problems under "real world" conditions.

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APPENDICES

APPENDIX I

Derivation of Variable Transformation for Multivariate Dependency

Multivariate Dependency

The derivation of the required transformation in the case of bivariate dependency is relatively simple, however, the same procedure becomes more complex as the number of dependent observations increases. The multivariate normal probability distribution is represented in matrix form as follows:

$$P(\mathbf{x}) = (2\pi)^{-.5k} |\Sigma|^{-.5} \exp{-.5((\mathbf{x}-\boldsymbol{\mu})`\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu}))}, \tag{14}$$

where k represents the number of measures taken within each family. The conditional probability is obtained by dividing equation (14) by the multivariate distribution of $x_2,\ldots,x_k$. Calculation of the multivariate conditional probability distribution requires that the exponent for equation (14) be subtracted from the exponent for the distribution of the determining variables x_2 through x_k. To carry this out we must first express Σ^{-1} as a symbolic function of the elements of Σ using the following formula:

$$\Sigma^{-1} = \frac{(\text{cofactor}(\Sigma))`}{\text{determinant}(\Sigma)}. \tag{15}$$

We will then be able to multiply the transposed, mean-centered x-matrices by the symbolic representations of the inverse covariance matrices, which are then multiplied again by the mean-centered x-matrices as indicated in equation (14). The resulting exponents must then be modified so that they have a common denominator and can be subtracted.

These computations are relatively simple in the case of a bivariate dependency, as attaining a common denominator requires only multiplying the exponent of the univariate multiple distribution by (1-r) before subtracting. The procedure is more complex when k

is equal to three as the symbolic determinant of the 3 by 3 covariance matrix is more complex:

$$\det(\Sigma_3) = \mathrm{var}^3(1-r^2_{12} - r^2_{13} - {}^2_{23} + 2r_{12}r_{13}r_{23}). \tag{16}$$

The symbolic exponent of the multivariate normal distribution when k=3 is

$$\begin{aligned}\text{exponent } (P(x_1,x_2,x_3)) = (-.5\det(\Sigma_3))^{-1}\ \mathrm{var}^2(x)\,[(1-r^2_{23})x^2_1 - 2x_1x_2(r_{12}-r_{13}r_{23}) \\ - 2x_1x_3(r_{13}-r_{12}r_{23}) - 2x_2x_3(r_{23}-r_{12}r_{13}) + (1-r^2_{13})x^2_2 + (1-r^2_{12})x^2_3].\end{aligned} \tag{17}$$

The determinant of the 2 by 2 covariance matrix of the determining variables is

$$\det(\Sigma_2) = \mathrm{var}^2(1-r^2_{23}), \tag{18}$$

and the symbolic exponent of the bivariate normal distribution of the determining variables is

$$\text{exponent } (P(x_2,x_3)) = (-.5\det(\Sigma_2))^{-1}\ \mathrm{var}(x)[x^2_2 - 2x_2x_3(r_{23}) + x^2_3]. \tag{19}$$

Before subtracting equation (17) from equation (19), a common denominator is formed as follows:

$$\det(\Sigma_2) \text{ exponent } (P_3) - \det(\Sigma_3) \text{ exponent } (P_2). \tag{20}$$

The resulting distribution reveals that the appropriate transformation when k=3 is:

$$x_t|_{k=3} = (1-r^2_{23})x_1 - (r_{12}-r_{13}r_{23})x_2 - (r_{13}-r_{12}r_{23})x_3. \tag{21}$$

The derivations of the appropriate transformations when k equals four or more interdependent observations are far too complex for manual computation, but could be carried out using math software which allows symbolic math computation.

APPENDIX II - MATLAB MODULES

```
**************SIMULATE DATA*****************************************

n=input('sample size?');
corr=input('error correlation?');
B1=[];
B2=[];
B3=[];
B4=[];
vary=[];
lof=[];
Crit=[];
z=zeros(15,1);

for i=1:100
x=randn(n,4);
randn('seed',sum(clock*1000000));
e=ones(n,1);
xbar=mean(x);
stdx=diag(std(x));
xor=(x-(e*xbar))*inv(stdx);
[n,q]=size(xor);

x1=xor(1:n,1);
x2=xor(1:n,2);
x3=xor(1:n,3);
x4=xor(1:n,4);

ey1=randn(n,1);
randn('seed',sum(clock*1000000));
e1bar=mean(ey1);
stde1=diag(std(ey1));
ey1=(ey1-(ones(n,1)*e1bar))*inv(stde1);
```

```
ey2=[];
for k=2:2:n
    t=ey1(k:-1:k-1,1);
    ey2=[ey2;t];
end

ey=ey1+(corr*ey2);

y=(.05*x2)+(.25*x3)+(.75*x4)+ey;

yp=[];
for k=2:2:n
    t=y(k:-1:k-1,1);
    yp=[yp;t];
end

data=[xor y yp]

******COMPUTE REGRESSION ESTIMATES AND INFORMATION CRITERIA********
Design=inv(x'*x);
Bhat=Design*x'*y;
Bhatstd=Bhat*inv(std(y));
Yhat=x*Bhat;
Resid=y-Yhat;

for v=1:n-1
Resid2=[];
for k=1:n-1
    t=Res(k+1,h);
    Resid2=[Resid2;t];
end
t=Res(1,h);
Resid2=[Resid2;t];
```

```
Res=[Res Resid2];
[n,h]=size(Res);
end

Resid2=[];
for k=2:2:n
    t=Resid(k:-1:k-1,1:p);
    Resid2=[Resid2;t];
end
Res=[Resid Resid2];
CovRes=cov(Res);

Ybar=mean(y);
Ybarsq=Ybar'*Ybar;
RSS=Resid'*Resid;
SSR=(Bhat'*x'*y)-(n*Ybarsq);
SSY=(y'*y)-(n*Ybarsq);
Rsqr=SSR/SSY;
Sighatsq=RSS/n;
CovBhat=kron(Sighatsq,Design);

CorrCovRes=(diag(diag(CovRes)))^(-1/2)*CovRes*(diag(diag(CovRes)))^(-
1/2);

CorrCovBhat=(diag(diag(CovBhat)))^(-
1/2)*CovBhat*(diag(diag(CovBhat)))^(-1/2);

Lackoffit=(n*p*log(2*pi))+(n*log(det(Sighatsq)))+(n*p);
CompCovBhat=((q*p)*(log(trace(CorrCovBhat)/(q*p))))-
log(det(CorrCovBhat));
CompCovRes=((2*p)*(log(trace(CorrCovRes)/(2*p))))-log(det(CorrCovRes));
CompCovPars=CompCovBhat+CompCovRes;
```

```
aic=Lackoffit+(2*q);

icomp=aic+CompCovPars;

Output=[icomp];
Crit=[Crit;Output];

end

**********************TABLE RESULTS**********************************
t1=t(2,1);
t2=t(3,1);
t3=t(4,1);
t4=t(5,1);

if t1>1.65 & t2>1.65 & t3>1.65 & t4>1.65
   z(1,1)=z(1,1)+1;
end
if t1>1.65 & t2>1.65 & t3>1.65 & t4<1.65
   z(2,1)=z(2,1)+1;
end
if t1>1.65 & t2>1.65 & t3<1.65 & t4>1.65
   z(3,1)=z(3,1)+1;
end
if t1>1.65 & t2<1.65 & t3>1.65 & t4>1.65
   z(4,1)=z(4,1)+1;
end
if t1<1.65 & t2>1.65 & t3>1.65 & t4>1.65
   z(5,1)=z(5,1)+1;
end
if t1>1.65 & t2>1.65 & t3<1.65 & t4<1.65
   z(6,1)=z(6,1)+1;
end
```

```
if t1>1.65 & t2<1.65 & t3>1.65 & t4<1.65
   z(7,1)=z(7,1)+1;
end
if t1>1.65 & t2<1.65 & t3<1.65 & t4>1.65
   z(8,1)=z(8,1)+1;
end
if t1<1.65 & t2>1.65 & t3>1.65 & t4<1.65
   z(9,1)=z(9,1)+1;
end
if t1<1.65 & t2>1.65 & t3<1.65 & t4>1.65
   z(10,1)=z(10,1)+1;
end
if t1<1.65 & t2<1.65 & t3>1.65 & t4>1.65
   z(11,1)=z(11,1)+1;
end
if t1>1.65 & t2<1.65 & t3<1.65 & t4<1.65
   z(12,1)=z(12,1)+1;
end
if t1<1.65 & t2>1.65 & t3<1.65 & t4<1.65
   z(13,1)=z(13,1)+1;
end
if t1<1.65 & t2<1.65 & t3>1.65 & t4<1.65
   z(14,1)=z(14,1)+1;
end
if t1<1.65 & t2<1.65 & t3<1.65 & t4>1.65
   z(15,1)=z(15,1)+1;
end

b1=Bhatstd(2,1);
B1=[B1;b1];
b2=Bhatstd(3,1);
B2=[B2;b2];
b3=Bhatstd(4,1);
```

```
B3=[B3;b3];
b4=Bhatstd(5,1);
B4=[B4;b4];
end

mean(B1)
std(B1)
mean(B2)
std(B2)
mean(B3)
std(B3)
mean(B4)
std(B4)

var=cov(y);
vary=[vary;var];
end

lack=Lackoffit;
lof=[lof;lack];
end

mean(vary)
std(vary)

mean(lof)
std(lof)

x=xor;

  [Y,I]=min(Crit);

  z(I,1)=(z(I,1))+1;
```

```
end
[n,q]=size(xor);
[Model,Ksub]=subset(q);
[Model z]

********************TRANSFORM DATA*****************************
   yp=[];                              %create empty vector for paired
                                          observations
   for k=2:2:n                         %begin loop
    t=y(k:-1:k-1,1);                   %pair each observation with
dependent
    yp=[yp;t];                            observation
   end

   ycorr=[y yp];                       %calculate correlation between
   covaryp=cov(ycorr);                    observations
   covyp=covaryp(2,1);                 %"       "        "
   stdy=std(y);                        %"       "        "
   stdyp=std(yp);                      %"       "        "
   r=covyp/(stdy*stdyp);               %"       "        "

   yt=y-(r*yp);                        %perform variable transformation

   y=yt;                               %redefine y
```

APPENDIX III - Effects of Observation Correlation

Table A-1. Effects of Observation Correlation; Sample Size=50; Parameters for Beta Distributions

	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
B1	.008 (.10)	.003 (.12)	.001 (.11)	.013 (.12)	.004 (.11)	.002 (.13)	.009 (.10)	.003 (.13)	.009 (.14)	.009 (.13)
B2	.025 (.11)	.035 (.11)	.034 (.12)	.034 (.12)	.046 (.12)	.034 (.11)	.058 (.11)	.043 (.12)	.024 (.12)	.038 (.12)
B3	.198 (.12)	.207 (.12)	.210 (.11)	.184 (.12)	.189 (.12)	.181 (.12)	.186 (.12)	.177 (.13)	.168 (.12)	.173 (.13)
B4	.584 (.07)	.590 (.09)	.579 (.08)	.571 (.09)	.572 (.10)	.561 (.10)	.538 (.11)	.505 (.10)	.498 (.10)	.487 (.10)

Table A-2. Effects of Observation Correlation; Sample Size=100; Parameters for Beta Distributions

	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
B1	.007 (.12)	.005 (.08)	.014 (.08)	.006 (.07)	.007 (.09)	.008 (.08)	.005 (.09)	.004 (.09)	.006 (.08)	.013 (.09)
B2	.040 (.08)	.050 (.08)	.046 (.08)	.039 (.09)	.030 (.08)	.026 (.08)	.021 (.09)	.030 (.09)	.039 (.08)	.038 (.09)
B3	.194 (.09)	.194 (.08)	.177 (.09)	.205 (.08)	.195 (.08)	.186 (.09)	.159 (.08)	.186 (.08)	.175 (.09)	.151 (.08)
B4	.580 (.06)	.584 (.06)	.582 (.05)	.569 (.06)	.562 (.06)	.558 (.06)	.532 (.07)	.513 (.07)	.501 (.07)	.475 (.08)

Table A-3. Effects of Observation Correlation; Sample Size=200; Parameters for Beta Distributions

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
B1	.001 (.06)	.005 (.06)	.006 (.06)	.001 (.05)	.004 (.06)	.003 (.06)	.004 (.06)	.003 (.06)	.012 (.07)	.004 (.06)
B2	.040 (.06)	.039 (.05)	.042 (.05)	.037 (.06)	.041 (.06)	.036 (.06)	.036 (.06)	.040 (.06)	.044 (.06)	.033 (.06)
B3	.188 (.06)	.191 (.05)	.202 (.05)	.185 (.05)	.187 (.05)	.185 (.06)	.166 (.07)	.167 (.06)	.162 (.06)	.164 (.06)
B4	.588 (.04)	.587 (.04)	.587 (.04)	.570 (.04)	.562 (.04)	.550 (.05)	.533 (.04)	.522 (.04)	.491 (.06)	.476 (.05)

Table A-4. Effects of Observation Correlation; Sample Size=500; Parameters for Beta Distributions

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
B1	.003 (.03)	.000 (.04)	.002 (.04)	.000 (.04)	.000 (.03)	.005 (.04)	.004 (.03)	.006 (.04)	.004 (.04)	.004 (.06)
B2	.042 (.04)	.040 (.04)	.037 (.04)	.044 (.04)	.040 (.03)	.035 (.04)	.033 (.03)	.032 (.04)	.047 (.04)	.033 (.06)
B3	.197 (.04)	.199 (.03)	.200 (.04)	.194 (.03)	.183 (.04)	.182 (.04)	.176 (.04)	.173 (.04)	.169 (.04)	.164 (.06)
B4	.584 (.02)	.586 (.02)	.578 (.02)	.568 (.03)	.561 (.03)	.548 (.03)	.532 (.03)	.513 (.03)	.499 (.03)	.476 (.05)

Table A-5. Effect of Observation Correlation; Sample Size=50; Significant Predictors in 100 Trials

	Error Correlation									
	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4	38%	37%	35%	44%	46%	46%	45%	53%	52%	46%
x12										
x13										
x14		2%	2%	1%			1%	3%	3%	1%
x23										
x24	4%	5%	6%	5%	4%	2%	6%	4%	4%	5%
x34	50%	52%	49%	44%	40%	46%	42%	32%	34%	40%
x123										
x124			1%		1%			1%		
x134	2%	2%	3%	2%	3%	6%		3%	3%	3%
x234	6%	2%	4%	4%	5%	3%	5%	4%	4%	4%
x1234					1%		1%			1%

Table A-6. Effect of Observation Correlation; Sample Size=100; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	20%	21%	27%	25%	19%	29%	36%	25%	33%	38%
x12										
x13										
x14	1%	1%			1%	2%	3%	1%	2%	2%
x23										
x24	1%	2%	2%	3%	3%	2%	1%	3%	3%	6%
x34	58%	54%	49%	61%	65%	58%	53%	56%	55%	46%
x123										
x124		1%								
x134	5%	6%	9%	2%	7%	3%	1%	6%	2%	3%
x234	13%	14%	12%	9%	4%	6%	5%	8%	4%	5%
x1234	2%	1%	1%		1%		1%	1%	1%	

Table A-7. Effect of Observation Correlation; Sample Size=200; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	3%	2%		2%	4%	8%	13%	12%	10%	15%
x12										
x13										
x14						2%		1%	1%	
x23										
x24								3%	2%	1%
x34	75%	78%	76%	80%	75%	71%	64%	68%	64%	66%
x123										
x124										
x134	4%	7%	7%	4%	5%	3%	6%	2%	5%	5%
x234	17%	13%	16%	13%	16%	13%	17%	14%	15%	11%
x1234	1%		1%	1%		3%			3%	2%

Table A-8. Effect of Observation Correlation; Sample Size=500; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4										
x12										
x13										
x14										1%
x23										
x24										1%
x34	63%	67%	67%	67%	67%	72%	80%	70%	62%	78%
x123										
x124										
x134	1%	2%	2%	2%	2%	3%	2%	4%	6%	7%
x234	35%	29%	29%	27%	31%	25%	18%	26%	31%	12%
x1234	1%	2%	2%	4%					1%	1%

APPENDIX IV - Regression Results for Transformed Data

Table A-11. Regression Results for Transformed Data; Sample Size=50; Significant Predictors in 100 Trials

	Error Correlation									
	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4	38%	37%	37%	44%	36%	30%	18%	30%	17%	20%
x12										
x13										
x14		2%	2%	2%		1%	1%		2%	2%
x23										
x24	4%	4%	5%	4%	1%	5%	2%	2%	3%	4%
x34	50%	48%	44%	44%	52%	52%	67%	57%	62%	62%
x123										
x124			2%	1%				1%		
x134	2%	1%	3%	2%	5%	1%	1%	1%	6%	3%
x234	6%	6%	7%	3%	5%	11%	10%	9%	8%	9%
x1234		2%			1%		1%		2%	

Table A-12. Regression Results for Transformed Data; Sample Size=100; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	20%	18%	14%	14%	14%	5%	5%	5%	3%	3%
x12										
x13										
x14	1%		1%	1%					1%	
x23										
x24	1%	3%	3%			3%		4%		1%
x34	58%	61%	66%	70%	64%	74%	74%	70%	78%	73%
x123										
x124					1%					
x134	5%	5%	10%	3%	4%	2%	6%	6%	4%	3%
x234	13%	11%	6%	12%	16%	14%	15%	15%	13%	18%
x1234	2%	2%			2%	2%			1%	2%

Table A-13. Regression Results for Transformed Data; Sample Size=200; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	3%	3%	1%	3%	3%	2%				
x12										
x13										
x14				1%		1%				
x23										
x24						1%				
x34	75%	76%	78%	73%	79%	63%	69%	74%	68%	67%
x123										
x124										
x134	4%	4%	2%	6%	4%	9%	4%	3%	4%	
x234	17%	16%	18%	14%	12%	22%	27%	21%	26%	31%
x1234	1%	1%	1%	3%	2%	2%		2%	2%	2%

Table A-14. Regression Results for Transformed Data; Sample Size=500; Significant Predictors in 100 Trials

	Error Correlation									
	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4										
x12										
x13										
x14										
x23										
x24										
x34	63%	66%	70%	63%	57%	61%	54%	54%	53%	46%
x123										
x124										
x134	1%	1%	2%	5%	1%	3%	4%	4%	3%	3%
x234	35%	29%	27%	31%	42%	36%	40%	42%	40%	51%
x1234	1%	4%	1%	1%			2%		4%	

APPENDIX V - Results for Autoregression Models

Table A-15. Results for Autoregression Models; Sample Size=50; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	35%	36%	41%	38%	28%	27%	15%	16%	14%	18%
x12										
x13										
x14	5%	2%	3%		1%	4%	2%	2%	1%	1%
x23										
x24	8%	5%	4%	1%	4%	3%	6%	4%	1%	2%
x34	45%	43%	42%	50%	55%	50%	58%	56%	68%	62%
x123										
x124		1%		1%	1%	1%		1%		
x134	2%	5%	4%	5%	6%	4%	3%	7%	5%	3%
x234	5%	7%	6%	5%	5%	10%	15%	14%	9%	12%
x1234		1%				1%	1%		2%	2%

Table A-16. Results for Autoregression Models; Sample Size=100; Significant Predictors in 100 Trials

	Error Correlation									
	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4	10%	15%	16%	9%	14%	10%	3%	4%	4%	1%
x12										
x13										
x14	1%	1%	2%							
x23										
x24	4%	2%	4%	1%		1%	1%	3%		
x34	68%	64%	66%	76%	73%	70%	81%	76%	73%	73%
x123										
x124						1%				
x134	5%	4%	3%	3%	3%	1%	5%	3%	3%	5%
x234	10%	13%	9%	10%	10%	16%	10%	14%	18%	20%
x1234	2%	1%		1%		1%			2%	1%

Table A-17. Results for Autoregression Models; Sample Size=200; Significant Predictors in 100 Trials

Error Correlation

	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4	1%	1%	4%		1%					
x12										
x13										
x14										
x23										
x24	1%		1%			1%				
x34	73%	75%	67%	78%	74%	74%	74%	70%	73%	67%
x123										
x124										
x134	6%	5%	2%	1%	2%	3%	4%	2%	2%	6%
x234	19%	18%	24%	21%	22%	18%	21%	28%	22%	25%
x1234		1%	2%		1%	4%	1%		3%	2%

Table A-18. Results for Autoregression Models; Sample Size=500; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4										
x12										
x13										
x14										
x23										
x24										
x34	69%	62%	69%	61%	66%	49%	56%	51%	52%	47%
x123										
x124										
x134	1%	4%	1%	2%	2%	2%	4%		2%	2%
x234	30%	34%	26%	35%	31%	48%	38%	48%	44%	49%
x1234			4%	2%	1%	1%	2%	1%	2%	2%

APPENDIX VI - Results for Structural Equation Models

Table A-19. Results for Structural Equation Model; Sample Size=200; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	8%		2%							
x12										
x13										
x14										
x23										
x24	2%									
x34	70%		66%		74%		76%		74%	
x123										
x124										
x134	8%		12%		10%		6%		9%	
x234	10%		16%		16%		18%		15%	
x1234	2%		4%						2%	

APPENDIX VII - Results for Akaike's Information Criteria (AIC)

Table A-20. Results for Akaike's Information Criterion (AIC); Sample Size=50; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	27%	17%	23%	24%	29%	28%	25%	40%	47%	30%
x12										
x13										
x14	4%	8%	9%	10%	4%	6%	7%	7%	1%	8%
x23										
x24	4%	12%	5%	7%	7%	5%	9%	10%	7%	9%
x34	38%	36%	42%	43%	35%	49%	42%	19%	29%	38%
x123										
x124	1%	1%	1%	3%	2%			2%	2%	3%
x134	10%	15%	9%	6%	11%	8%	8%	8%	5%	6%
x234	13%	7%	8%	4%	6%	4%	8%	12%	9%	5%
x1234	3%	4%	3%	3%	6%		1%	2%		

Table A-21. Results for Akaike's Information Criterion (AIC); Sample Size=100; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	11%	12%	9%	11%	11%	22%	22%	21%	22%	20%
x12										
x13										
x14	1%	1%	3%	1%	2%	2%	3%	4%		3%
x23										
x24	3%	2%	3%	2%	6%	2%	2%	4%	4%	7%
x34	50%	59%	63%	49%	53%	45%	52%	47%	47%	41%
x123										
x124		1%	1%		1%			3%	1%	
x134	16%	12%	7%	15%	11%	13%	4%	10%	10%	7%
x234	15%	12%	10%	21%	13%	15%	15%	11%	15%	16%
x1234	4%	1%	4%	1%	3%	1%	2%		1%	6%

Table A-22. Results for Akaike's Information Criterion (AIC); Sample Size=200; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	1%	2%	2%	3%	2%	3%	4%	2%	9%	7%
x12										
x13										
x14	1%		1%			1%		1%	2%	
x23										
x24					1%			2%	3%	1%
x34	60%	66%	61%	68%	56%	60%	56%	57%	46%	58%
x123										
x124										
x134	15%	8%	17%	8%	15%	15%	15%	12%	14%	8%
x234	20%	21%	15%	17%	21%	18%	22%	22%	24%	22%
x1234	3%	3%	4%	4%	5%	3%	3%	4%	2%	4%

Table A-23. Results for Akaike's Information Criterion (AIC); Sample Size=500; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4										
x12										
x13										
x14										
x23										
x24										
x34	52%	59%	56%	52%	55%	54%	58%	55%	58%	63%
x123										
x124										
x134	15%	7%	14%	9%	11%	14%	12%	11%	13%	15%
x234	28%	29%	25%	31%	25%	31%	26%	29%	27%	19%
x1234			4%	2%	1%	1%	2%	1%	2%	2%

APPENDIX VIII - Results for Information Complexity (ICOMP)

Table A-24. Results for Information Complexity (ICOMP); Sample Size=50; Significant Predictors in 100 Trials

	Error Correlation									
	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4	25%	16%	24%	34%	32%	36%	28%	26%	29%	39%
x12										
x13										
x14	3%	7%	6%	2%	3%	6%	2%	17%	9%	10%
x23										
x24	5%	7%	5%	5%	3%	6%	10%	9%	13%	9%
x34	43%	44%	41%	43%	42%	41%	35%	29%	20%	17%
x123										
x124	1%	2%	1%	3%	1%			1%	2%	3%
x134	9%	8%	15%	8%	11%	6%	8%	9%	8%	9%
x234	9%	13%	6%	4%	8%	3%	11%	7%	16%	9%
x1234	5%	3%	2%	1%		2%	5%	2%	3%	1%

Table A-25. Results for Information Complexity (ICOMP); Sample Size=100; Significant Predictors in 100 Trials

	Error Correlation									
	.00	**.10**	**.20**	**.30**	**.40**	**.50**	**.60**	**.70**	**.80**	**.90**
x1										
x2										
x3										
x4	4%	8%	5%	8%	11%	21%	11%	22%	31%	26%
x12										
x13										
x14	3%	2%	4%	3%	1%	3%	7%	2%	6%	5%
x23										
x24	2%	1%	1%	2%	2%	3%	5%	9%	7%	4%
x34	62%	60%	65%	61%	49%	50%	51%	39%	34%	36%
x123										
x124		1%			1%		1%	2%	1%	1%
x134	9%	14%	11%	13%	17%	10%	14%	10%	11%	8%
x234	16%	12%	10%	12%	13%	12%	9%	13%	9%	16%
x1234	4%	2%	4%	1%	6%	1%	2%	3%	1%	4%

Table A-26. Results for Information Complexity (ICOMP); Sample Size=200; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4				6%	2%	3%	2%	12%	15%	19%
x12										
x13										
x14							1%	1%	1%	
x23										
x24		1%			1%	2%		2%		6%
x34	53%	59%	58%	65%	60%	61%	62%	54%	49%	45%
x123										
x124										
x134	16%	12%	12%	8%	11%	13%	9%	9%	15%	9%
x234	26%	22%	24%	18%	18%	19%	23%	18%	16%	19%
x1234	5%	6%	6%	3%	7%	2%	3%	4%	4%	1%

Table A-27. Results for Information Complexity (ICOMP); Sample Size=500; Significant Predictors in 100 Trials

Error Correlation

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4										
x12										
x13										
x14										
x23										
x24										
x34	50%	53%	58%	59%	47%	52%	54%	61%	58%	56%
x123										
x124										
x134	10%	5%	7%	11%	12%	8%	7%	12%	15%	14%
x234	33%	36%	29%	27%	37%	36%	32%	20%	21%	27%
x1234	7%	6%	6%	3%	4%	4%	7%	7%	6%	3%

APPENDIX IX - Results for ICOMP with Autoregression

Table A-28. Results for ICOMP and Autoregression (ICOMP/VAR); Sample Size=50; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	22%	29%	25%	11%	19%	15%	13%	14%	9%	5%
x12										
x13										
x14	6%	5%	4%	8%	5%	5%	3%		1%	2%
x23										
x24	5%	6%	3%	4%	2%		3%	1%		4%
x34	46%	35%	41%	53%	53%	52%	51%	51%	51%	57%
x123										
x124				1%		1%				
x134	7%	11%	7%	8%	9%	8%	12%	14%	13%	7%
x234	13%	12%	10%	14%	8%	16%	13%	18%	25%	20%
x1234	1%	2%	11%	1%	4%	3%	5%	2%	1%	5%

Table A-29. Results for ICOMP and Autoregression (ICOMP/VAR); Sample Size=100; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4	8%	4%	7%	7%	1%	6%	5%	3%		2%
x12										
x13										
x14	13%	1%	1%		1%	1%		1%	1%	
x23										
x24	2%	4%	1%		2%	3%	1%			
x34	49%	58%	53%	64%	61%	58%	62%	47%	56%	63%
x123										
x124		1%	1%		1%					
x134	11%	11%	9%	10%	16%	10%	8%	11%	13%	12%
x234	19%	17%	22%	14%	15%	15%	18%	34%	25%	18%
x1234	7%	4%	3%	5%	3%	7%	6%	4%	5%	5%

Table A-30. Results for ICOMP and Autoregression (ICOMP/VAR); Sample Size=200; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4		1%					1%			
x12										
x13										
x14				2%						
x23										
x24		1%		1%						
x34	66%	61%	62%	64%	66%	67%	52%	52%	49%	51%
x123										
x124										
x134	14%	6%	10%	9%	8%	9%	15%	13%	9%	7%
x234	16%	30%	27%	22%	22%	22%	30%	24%	25%	23%
x1234	4%	1%	1%	2%	4%	2%	2%	11%	17%	19%

Table A-31. Results for ICOMP and Autoregression (ICOMP/VAR); Sample Size=500; Significant Predictors in 100 Trials

	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90
x1										
x2										
x3										
x4										
x12										
x13										
x14										
x23										
x24										
x34	49%	47%	47%	44%	64%	41%	32%	42%	49%	39%
x123										
x124										
x134	16%	9%	10%	6%	4%	12%	9%	7%	5%	2%
x234	29%	39%	41%	40%	29%	38%	47%	43%	39%	50%
x1234	8%	5%	2%	10%	3%	9%	12%	8%	7%	9%

APPENDIX X - Results by Analytic Technique Using National Survey of Children Data

Table A-32. Regression Results for Influence of Parental Variables on Child Outcomes by Method of Correcting for Observation Interdependence (NSC data); Never Poor Subsample

Outcome	No Correction	Structural Equations	AIC
A. Low Attain.			
Father Inv.			
Emotional	-.007	-.053	.007
Behavioral	.016	.040	.016
Mother Inv.			
Emotional	-.015	-.073	-.015
Behavioral	.064	.834**	.064[a]
N	563	563	563
Adjusted R^2	.377		189.44
B. Delinquency			
Father Inv.			
Emotional	.108	.032	.108[a]
Behavioral	-.028	-.007	.028
Mother Inv.			
Emotional	-.144**	-.874**	-.144[a]
Behavioral	.018	.086	.018
N	563	563	563
Adjusted R^2	.058		193.77
C. Depression			
Father Inv.			
Emotional	.094	-.557*	-.094[a]
Behavioral	-.059	-.075	-.059
Mother Inv.			
Emotional	.082	.361*	.082
Behavioral	.019	-.008	.019
N	563	563	563
Adjusted R^2	.035		389.72

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-33. Regression Results for Influence of Parental Variables on Child Outcomes by Method of Correction for Observation Interdependence (NSC data); Temporarily Poor Subsample

Outcome	No Correction	Structural Equations	AIC
A. Low Attain.			
Father Inv.			
Emotional	.155	.143*	155
Behavioral	.180	.684**	.180[a]
Mother Inv.			
Emotional	.134	.108	134[a]
Behavioral	-.054	.065	-.054
N	108	108	108
Adjusted R^2	.405		342.16
B. Delinquency			
Father Inv.			
Emotional	-.207	-.265	-.207[a]
Behavioral	-.123	-.421*	-.123[a]
Mother Inv.			
Emotional	-.085	-.008	-.085
Behavioral	.167	.305	.167
N	108	108	108
Adjusted R^2	.106		410.20
C. Depression			
Father Inv.			
Emotional	-.197	-.190	-.197[a]
Behavioral	.055	.053	.055
Mother Inv.			
Emotional	-.140	-.645	-.140
Behavioral	.064	.112	.064
N	108	108	108
Adjusted R^2	.019		776.83

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-34. Regression Results for Influence of Parental Variables on Child Outcomes by Method of Correction for Observation Interdependence (NSC data); Persistently Poor Subsample

Outcome	No Correction	Structural Equations	AIC
A. Low Attain.			
Father Inv.			
Emotional	.128	.445*	.128
Behavioral	-.164	.249	-.164
Mother Inv.			
Emotional	.160	-.056	.160
Behavioral	.397**	.250	.397[a]
N	72	72	72
Adjusted R^2	.393		235.24
B. Delinquency			
Father Inv.			
Emotional	-.080	.002	-.080
Behavioral	-.211	-.063	-.211[a]
Mother Inv.			
Emotional	-.324*	-.869*	-.324[a]
Behavioral	.095	-.068	-.095
N	72	72	72
Adjusted R^2	.044		113.15
C. Depression			
Father Inv.			
Emotional	-.362*	-.529*	-.362[a]
Behavioral	.146	-.102	.146[a]
Mother Inv.			
Emotional	-.051	-.018	-.051
Behavioral	.131	.352*	.131
N	72	72	72
Adjusted R^2	.018		551.56

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-35. Regression Results for Influence of Parental Variables on Child Outcomes by Method of Accounting for Observation Interdependence (NSC data); No Welfare Subsample

Outcome	No Correction	Structural Equations	AIC
A. Low Attain.			
Father Inv.			
Emotional	-.063	-.048	-.063
Behavioral	.108	.162	.108[a]
Mother Inv.			
Emotional	.012	.123*	.012
Behavioral	.027	.668**	.027
N	627	627	627
Adjusted R^2	.402		212.47
B. Delinquency			
Father Inv.			
Emotional	-.016	.013	-.016
Behavioral	-.106	-.168	-.106[a]
Mother Inv.			
Emotional	-.127**	-.819**	-.127[a]
Behavioral	.042	.002	.042
N	627	627	627
Adjusted R^2	.066		219.47
C. Depression			
Father Inv.			
Emotional	-.137	-.258*	-.137[a]
Behavioral	-.048	-.035	-.048
Mother Inv.			
Emotional	.090	.497*	.090
Behavioral	.164	-.211	.164[a]
N	627	627	627
Adjusted R^2	.019		437.45

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A- 36. Regression Results for Influence of Parental Variables on Child Outcomes by Method of Correction for Observation Interdependence (NSC data); Received Welfare Subsample

Outcome	No Correction	Structural Equations	AIC
A. Low Attain.			
Father Inv.			
Emotional	-.014	.227*	-.014
Behavioral	-.027	.233*	-.027
Mother Inv.			
Emotional	.279***	.457**	.279[a]
Behavioral	.021	.084	.021
N	117	117	117
Adjusted R^2	.484		406.96
B. Delinquency			
Father Inv.			
Emotional	-.132	-.501*	-.132
Behavioral	-.013	.148	.013
Mother Inv.			
Emotional	.097	.093	.097
Behavioral	.063	.258	.063
N	117	117	117
Adjusted R^2	052		329.52
C. Depression			
Father Inv.			
Emotional	-.044	.118	-.044
Behavioral	.069	-.064	.069
Mother Inv.			
Emotional	-.210*	- 707*	-.210[a]
Behavioral	.237*	.112	.237[a]
N	117	117	117
Adjusted R^2	.067		861.59

a - Denotes that this predictor was included in the best model as selected by AIC.

APPENDIX XI: Regression Results by Sampling Strategy Using National Survey of Children Data

Table A-37. Regression Results for Influence of Parental Variables on Child Outcomes by Sampling Strategy (NSC data); Never Poor Subsample

Outcome	Multiple Measures (Str.Eq.)	Multiple Measures (AIC)	Youngest/ Onlies	Oldest/ Onlies	Random Selection
A. Low Attain.					
Father Inv.					
Emotional	-.053	.007	-.022	.000	-.005
Behavioral	.040	.016	.009	.032	.005
Mother Inv.					
Emotional	-.073	-.015	-.032	-.011	-.013
Behavioral	.834**	.064[a]	.118*	.055	.077†
N	563	563	433	433	433
Adjusted R^2		189.44	.392	.358	.379
B. Delinquency					
Father Inv.					
Emotional	.032	.108[a]	.010	.037	.026
Behavioral	-.007	.028	.013	-.013	-.032
Mother Inv.					
Emotional	-.874**	-.144[a]	-.136*	-.166**	-.136
Behavioral	.086	.018	.050	-.006	.026
N	563	563	433	433	433
Adjusted R^2		193.77	.063	.048	.049
C. Depression					
Father Inv.					
Emotional	-.557*	-.094[a]	.109	.071	.116
Behavioral	-.075	-.059	-.085	-.050	-.075
Mother Inv.					
Emotional	-.361*	.082	.086	.111*	.124
Behavioral	-.008	.019	-.002	.012	-.032
N	563	563	433	433	433
Adjusted R^2		389.72	.038	.049	.061

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-38. Regression Results for Influence of Parental Variables on Child Outcomes by Sampling Strategy (NSC data); Temporarily Poor Subsample

Outcome	Multiple Measures (Str. Eq.)	Multiple Measures (AIC)	Youngest /Onlies	Oldest/ Onlies	Random Selection
A. Low Attain.					
Father Inv.					
Emotional	-.143*	-.155	-.199	-.160	-.297
Behavioral	.684**	.180[a]	.216	.152	.303
Mother Inv.					
Emotional	.108	.134[a]	.157	.159	.249
Behavioral	.065	-.054	-.070	-.050	-.114
N	108	108	81	81	81
Adjusted R^2		342.16	.380	.412	.410
B. Delinquency					
Father Inv.					
Emotional	-.265	-.207[a]	.091	.207	.132
Behavioral	-.421*	.123[a]	-.163	-.333*	-.266
Mother Inv.					
Emotional	-.008	-.085	-.130	.027	.041
Behavioral	.305	.167	.200	-.021	-.016
N	108	108	81	81	81
Adjusted R^2		410.20	.063	.141	.119
C. Depression					
Father Inv.					
Emotional	-.190	-.197[a]	-.242	.262	-.007
Behavioral	.053	.055	.546**	.092	.272
Mother Inv.					
Emotional	-.645	-.140	-.219	-.060	-.184
Behavioral	.112	.064	.063	-.003	.121
N	108	108	81	81	81
Adjusted R^2		776.83	.067	.018	.046

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-39. Regression Results for Influence of Parental Variables on Child Outcomes by Sampling Strategy (NSC data); Persistently Poor Subsample

Outcome	Multiple Measures (Str. Eq.)	Multiple Measures (AIC)	Youngest/ Onlies	Oldest/ Onlies	Random Selection
A. Low Attain.					
Father Inv.					
Emotional	.445*	.128	.147	.165	.192
Behavioral	.249	.164	.114	.222	.217
Mother Inv.					
Emotional	.250	.160	.369*	.332*	.341
Behavioral	-.056	.397[a]	.160	.296	.340
N	72	72	51	51	51
Adjusted R^2		235.24	.341	.366	.371
B. Delinquency					
Father Inv.					
Emotional	.002	-.080	-.135	-.287	-.165
Behavioral	-.063	-.211[a]	-.198	-.355	-.330
Mother Inv.					
Emotional	-.068	-.324[a]	-.103	-.150	-.143
Behavioral	-.869*	-.095	-.306	-.518**	-.445
N	72	72	51	51	51
Adjusted R^2		113.15	.027	.180	.071
C. Depression					
Father Inv.					
Emotional	-.529*	-.362[a]	-.304	-.275	-.116
Behavioral	-.102	-.146[a]	.071	-.109	.083
Mother Inv.					
Emotional	-.018	-.051	-.083	.132	.122
Behavioral	.352*	.131	.173	.021	-.015
N	72	72	51	51	51
Adjusted R^2		551.56	.032	.063	.029

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-40. Regression Results for Influence of Parental Variables on Child Outcomes by Sampling Strategy (NSC data); No Welfare Subsample

Outcome	Multiple Measures (Str. Eq.)	Multiple Measures (AIC)	Youngest/ Onlies	Oldest/ Onlies	Random Selection
A. Low Attain.					
Father Inv.					
Emotional	-.048	-.063	.073	-.033	-.058
Behavioral	.162	.108[a]	-.092	.032	.033
Mother Inv.					
Emotional	.123*	.012	.058	.015	.023
Behavioral	.668**	.027	.009	.033	.038
N	627	627	483	483	483
Adjusted R^2		212.47	.396	.373	.391
B. Delinquency					
Father Inv.					
Emotional	.013	-.016	-.026	.015	.009
Behavioral	-.168	-.106[a]	.039	.006	-.012
Mother Inv.					
Emotional	-.819**	-.127[a]	.072	-.144**	-.119
Behavioral	.002	.042	-.121*	-.002	.030
N	627	627	483	483	483
Adjusted R^2		219.47	.072	.055	.061
C. Depression					
Father Inv.					
Emotional	-.258*	-.137[a]	-.127*	.045	-.099
Behavioral	-.035	-.048	-.102	-.009	-.065
Mother Inv.					
Emotional	.497*	.090	.090	.136*	.131
Behavioral	-.211	.164[a]	-.036	-.041	-.061
N	627	627	483	483	483
Adjusted R^2		437.45	.025	.029	.032

a - Denotes that this predictor was included in the best model as selected by AIC.

Table A-41. Regression Results for Influence of Parental Variables on Child Outcomes by Sampling Strategy (NSC data); Welfare Received Subsample

Outcome	Multiple Measures (Str. Eq.)	Multiple Measures (AIC)	Youngest/Onlies	Oldest/ Onlies	Random Selection
A. Low Attain.					
Father Inv.					
Emotional	.227*	-.014	-.007	-.063	-.073
Behavioral	.233*	-.027	-.062	.045	.050
Mother Inv.					
Emotional	.457*	.279[a]	.267**	.240*	.250
Behavioral	.084	.021	.027	.029	.035
N	117	117	83	83	83
Adjusted R^2		406.96	.502	.489	.492
B. Delinquency					
Father Inv.					
Emotional	-.501*	-.132	-.115	-.331*	-.267
Behavioral	.148	.013	-.007	.067	.068
Mother Inv.					
Emotional	.093	.097	.095	.126	.149
Behavioral	.258	.063	.050	.046	-.038
N	117	117	83	83	83
Adjusted R^2		329.52	.044	.068	.036
C. Depression					
Father Inv.					
Emotional	.118	-.044	.105	.091	.159
Behavioral	-.064	.069	.008	.000	-.017
Mother Inv.					
Emotional	-.707*	-.210[a]	-.298*	-.138	-.145
Behavioral	.112	.237[a]	.329*	.238	.241
N	117	117	83	83	83
Adjusted R^2		861.59	.145	.081	.096

a - Denotes that this predictor was included in the best model as selected by AIC.

VITA

Carol Bruce received her Master's degree in Child and Family Studies from the University of Tennessee, Knoxville in December, 1997. She has also earned an Associate's degree in Early Childhood Education from Montgomery College in Rockville, Maryland, and a Bachelor's degree in Family and Community Development from the University of Maryland.

Before coming to UTK, Carol had worked in child care as a teacher, and later as a director of a large center in Tucson, Arizona. After several years in this field, Carol worked in several agencies as a counselor with youth and families.

It was during a workshop on analytical reasoning, co-taught by Dr. Greer Fox and Dr. Cheryl Buehler, that Carol first became interested in learning more statistics. After exploring what the Statistics Department at UTK had to offer, she decided to pursue a concurrent Master's degree in Statistics, while also pursuing her doctorate in Human Ecology.

This dissertation reflects a synthesis of what Carol has learned from the two programs. She has sought to bring meaning to the statistical knowledge she has gained through its application to family issues, while also improving the study of family through more sophisticated statistical technique.

Carol is grateful for the many experiences that she has had while at UTK, and hopes to be able to use the skills she has developed to make significant contributions to our understanding of families.