Symmetry in Flows Among Reported Victimization Classifications with Nonresponse

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ABSTRACT

The United States' National Crime Survey is a large-scale, household survey used to provide estimates of victimizations. The National Crime Survey uses a rotating panel design under which sampled housing units are maintained in the sample for three-and-one-half years with residents of the housing units being interviewed every six months. Nonresponse is a serious problem in longitudinal data from the National Crime Survey since as few as 25% of all individuals interviewed for the survey are respondents over an entire three-and-one-half-year period. In addition, the nonresponse typically does not occur at random with respect to victimization status. This paper presents models for gross flows among two types of victimization reporting classifications: number of victimizations and seriousness of victimization. The models allow for random or nonrandom nonresponse mechanisms, and allow the probabilities underlying the gross flows to be either unconstrained or symmetric. The models are fit, using maximum likelihood estimation, to the data from the National Crime Survey.

KEY WORDS: Categorical data; Ignorable nonresponse; Longitudinal survey; National Crime Survey; Nonignorable nonresponse.

1. INTRODUCTION

The United States' National Crime Survey (NCS) is a large-scale, household survey conducted by the U.S. Bureau of the Census for the Bureau of Justice Statistics. Data from the NCS is used to produce quarterly estimates of victimization rates and yearly estimates of the prevalence of crime. The survey uses a rotating panel of housing units (HU's) under which individuals living in sampled HU's are interviewed up to seven times at six-month intervals.

Individuals interviewed for the NCS are asked about crimes committed against them or against their property in the previous six months. In this work, we begin to explore the victimization status reported by households (HH's) within sampled HU's from one interview to the next. Victimization status for a HH will be considered in two ways: by the number of crimes reported (zero, one, and two or more) and by the type of crime reported (no crime, property crime, and personal contact crime).

Since responses are not available from one NCS interview period to the next for all HH's, we must decide how to handle missing observations. The nonresponse problem is a serious problem in the longitudinal data available from the NCS. For example, Fienberg (1980) noted that complete, three-and-one-half-year records of NCS interviews are available for as few as 25% of all individuals interviewed. In addition, the nonresponse typically does not occur at random with respect to victimization status (see, for example, Saphire (1984)).

This work extends the models developed by Stasny (1986) for nonrandom nonresponse in estimating gross flows. In particular, the models presented here allow for symmetry in the matrix of flows among victimization classifications as well as allowing for completely random nonresponse, ignorable nonrandom nonresponse, or nonignorable nonresponse.

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Section 2 of this paper provides a brief description of the NCS and the longitudinal data from the survey. Section 3 gives a general form of the models for symmetry in gross flow matrices with missing data and presents iterative procedures for obtaining maximum likelihood estimators (MLE's) for the parameters of the models. Section 4 describes the fits of the models to data from the NCS. Section 5 presents conclusions and suggests areas for future research.

2.   THE NATIONAL CRIME SURVEY AND DATA

2.1   Survey Design

The NCS is a stratified, multi-stage, cluster sample of HU's. The survey was begun in July 1972 by the Law Enforcement Assistance Administration but has been administered by the Bureau of Justice Statistics since December 1979. The target population for the NCS is the civilian, non-institutionalized population of persons aged 12 and over living in housing units. The survey provides information on personal and household crimes committed against the individuals in sampled HU's. The following crimes and attempted crimes are covered by the NCS: assault, auto or motor vehicle theft, burglary, larceny, rape, and robbery. Crimes not covered by the survey include kidnapping, murder, shoplifting, and crimes that occur at places of business.

The NCS uses a rotating panel design under which a sampled HU is maintained in the sample for three and one-half years with interviews conducted at six-month intervals for a total of seven possible interviews. The initial interview at each HU, however, serves as a bounding interview and is not used for the purpose of estimation. Although there is a six-month interval between interviews at any one HU, NCS interviews are conducted in every month of the year; in order to make efficient use of trained interviewers, one-sixth of the HU's in the sample are scheduled for interviews each month. Since the sampling unit for the NCS is the HU, no attempt is made to follow individuals who move away from the HU during the three-and-one-half-year period. Rather, new individuals entering the HU are included in the survey. Each different group of individuals who live in a HU during its time in the NCS sample is considered a separate HH.

NCS interviews are conducted for all individuals 12 years of age or older who live in the sampled HU at the time of the interview. During the interview, individuals are asked about crimes committed against them or against the household in the previous six months. A single HH respondent is asked a series of six screening questions to elicit information on crimes committed against the HH (burglary, larceny, and motor vehicle theft). Then an eleven-question screener is used to elicit information from each individual in the HH concerning personal crimes committed against that individual (assault, rape, and robbery). An incident report is completed for each crime mentioned in response to the screening questions.

Additional information on the design and history of the NCS is provided, for example, by the U.S. Department of Justice and Bureau of Justice Statistics (1981), Saphire (1984), Dodge and Skogan (1987), and Montagliani (1987). A new sample design for the NCS has been used since January 1986. Taylor (1987) describes the redesign of the NCS and research associated with the redesign effort. The data used in this work, however, were collected under the original NCS design.

2.2   The Longitudinal Data

The data used in this work are from a large, longitudinal data set which includes all the regular NCS interview information collected from January 1975 to June 1979 except for the HU's that rotated into the sample in 1979. To make it easier to handle the data, this research uses only a subset of the data. The subset was created by taking a random start at the record

for the eighth HU in the full data set and then every fifteenth record after that. The resulting data set contains NCS records for 12,432 HU's. Because the HU's on the original longitudinal file are ordered in such a way that units from the same cluster appear together, the 1-in-15 systematic sample should not include two or more HU's from a single cluster. Thus, this research does not consider the problem of correlations among HU's within clusters.

2.3 Flows Among Victimization Classifications

The hierarchical, longitudinal data were used to create summary matrices for the years 1975, 1976, 1977, and 1978 showing flows among reported victimization classifications from each HH's first interview in a year to the HH's second interview for the year. Note that, since NCS interviews are conducted every month of the year, the first interview may occur at any time from January through June and the second interview may occur in July through December. Depending on the month of the interview, the victimizations reported in the first interview are those that occurred between the previous July and May while those reported in the second interview occurred between January and November. Thus, the analysis here explores only the reporting of crimes from one interview to the next. It cannot, for example, address issues of change in victimization reporting at various times of the year except in a very general sense.

It should be noted that during the time when the data were collected, a reference-period experiment was conducted using a sample of NCS HU's. Since individuals in HU's included in the experiment were asked to report victimizations for reference periods other than the usual six-month period, those HU's were not used in this analysis.

For the analyses here, each HH interviewed at least once during a given year was classified according to its reporting and victimization status at the two interview times. A victimization may have been reported by any member of the HH and may be against an individual or against the HH. Two sets of matrices showing victimization classifications are used in the analyses of Section 4. The matrices are given in Appendix I.

The first set of matrices show cross-classifications of HH's by the number of victimizations reported in the first and second interviews for each year. The classifications are: crime free (no victimizations reported), single crime (one victimization reported), multiple crime (two or more victimizations reported), and missing (HH did not respond or rotated out of the sample). The second set of matrices show cross-classifications of HH's by the type of victimization reported. The classifications are: crime free, property crime (burglary, larceny, and motor vehicle theft), contact crime (rape, assault, robbery, purse snatching, and pocket picking), and missing. These type-of-crime groupings are the same as those used in the NCS. In cases where multiple crimes were reported by a single HH, the classification used is for the most serious crime reported (contact crimes are taken to be more serious than property crimes).

Notice the large amount of nonresponse in the observed matrices shown in Appendix I. Only about 50% of the HH's who responded in at least one of the two interviews responded at both interview periods. The models presented in the following section, will allow us to handle this nonresponse while exploring the structure of the underlying matrix of probabilities of flows among the victimization classifications.
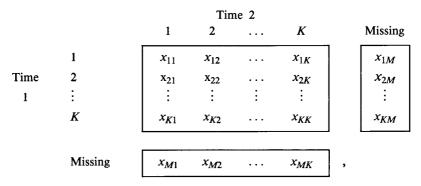
3. THE MODELS

This section presents a general form of the models that will be used to explore gross flows among victimization classifications in the NCS data. The form of the models follows that proposed by Chen and Fienberg (1974) for contingency tables with completely and partially classified data. The models for nonresponse are those developed by Stasny (1986) as well as

a model for random nonresponse. The model for symmetry in the flows, however, does not appear in the previous work. The models are presented in a general form because they are applicable to problems other than estimating gross flows among victimization classifications using NCS data.

3.1 Model for the Observed Data

Consider observation units that respond to a survey in at least one of two interview periods. Suppose that, when a unit responds to the survey, that unit is classified into one of K classifications. If a unit does not respond to the survey, that unit is classified as missing. Then the interview-to-interview flow data may be represented as in Table 1.

Table 1
Summary of Observed Data

		Time 2				
		1	2	...	K	Missing
	1	x_{11}	x_{12}	...	x_{1K}	x_{1M}
Time	2	x_{21}	x_{22}	...	x_{2K}	x_{2M}
1	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	K	x_{K1}	x_{K2}	...	x_{KK}	x_{KM}
Missing		x_{M1}	x_{M2}	...	x_{MK}	,

where x_{ij} = number of units with survey or missing status i at time 1 and j at time 2.

We suppose that each unit would fall into one of the cells of the $K \times K$ matrix of survey classifications if it were observed at both interview times. Let p_{ij} be the probability that a unit has status i at time 1 and status j at time 2, where i and j take on the values 1, 2, ..., K. Each unit in the (i,j) cell of the matrix of survey classifications has a chance of being missing at one of the two survey times. Let λ_{tij} be the probability that a unit in the (i,j) cell loses its classification at time t and, hence, is classified as missing at that time. Then the probabilities underlying the observed data are as shown in Table 2.

Table 2
Probabilities Underlying Observed Data

		Time 2				
		1	2	...	K	Missing
Time	1					
	2					
1	$\vdots$	$\left\{(1 - \lambda_{1ij} - \lambda_{2ij})p_{ij}\right\}$				$\left\{\sum_{j=1}^{K} p_{ij}\lambda_{2ij}\right\}$
	K					
Missing		$\left\{\sum_{i=1}^{K} p_{ij}\lambda_{1ij}\right\}$				.

Assuming that the p_{ij} are probabilities from a multinomial distribution, the likelihood function for the observed data is proportional to

$$\left\{ \prod_{i=1}^{K} \prod_{j=1}^{K} \left[p_{ij} (1 - \lambda_{1ij} - \lambda_{2ij}) \right]^{x_{ij}} \right\}$$

$$\times \left\{ \prod_{i=1}^{K} \left[\sum_{j=1}^{K} p_{ij} \lambda_{2ij} \right]^{x_{iM}} \right\}$$

$$\times \left\{ \prod_{j=1}^{K} \left[\sum_{i=1}^{K} p_{ij} \lambda_{1ij} \right]^{x_{Mj}} \right\}.$$

There are $3K^2 + 2K - 1$ free parameters defined above and only $K^2 + 2K$ observed cells of data with a single constraint on the total sample size. Thus there are too many parameters to estimate using the observed data and we must reduce the number of parameters in the model. In the following we reduce the number of parameters to be estimated by considering two models for the p_{ij}-parameters and six models for the λ_{tij}-parameters.

3.2 Models for the p and λ Probabilities

We consider two models for the p_{ij}'s, the probabilities of flows among survey classifications: the unconstrained model and the model of symmetric flows. Under the model of unconstrained flow probabilities, there is a different probability, p_{ij}, for every (i,j) cell of the flow matrix. Under the model of symmetric flows, we have $p_{ij} = p_{ji}$ for $i \neq j$ so that the probability that a unit has survey classification i at time 1 and j at time 2 is the same as the probability that a unit has survey classification j at time 1 and i at time 2. Note that symmetry in the cell probabilities of the flow matrix implies equality of row and column marginal totals. Thus the model of symmetry in flow probabilities implies a certain stability in the population since the expected number of units with a particular survey classification at time 1 is the same as the number with that classification at time 2.

As defined above, the λ_{tij}'s, the probabilities that units with survey classifications i at time 1 and j at time 2 are missing at time t, depend on the time at which the nonresponse occurs and on the survey classifications at both times 1 and 2. We consider six simpler models for these probabilities. These models, along with the associated degrees of freedom under both models for the p_{ij}, are given below:

	d.f. unconstrained p_{ij}	d.f. symmetric p_{ij}
Model R: $\lambda_{tij} = \lambda,$	$2K - 1$	$(K^2 + 3K - 2)/2$
Model A: $\lambda_{1ij} = \lambda_{1j}, \lambda_{2ij} = \lambda_{2i},$	0	$(K^2 - K)/2$
Model B: $\lambda_{tij} = \lambda_t,$	$2K - 2$	$(K^2 + 3K - 4)/2$
Model C: $\lambda_{1ij} = \lambda_j, \lambda_{2ij} = \lambda_i,$	K	$(K^2 + K)/2$
Model D: $\lambda_{1ij} = \lambda_{1i}, \lambda_{2ij} = \lambda_{2j},$	0	$(K^2 - K)/2$
Model E: $\lambda_{1ij} = \lambda_i, \lambda_{2ij} = \lambda_j,$	K	$(K^2 + K)/2$

Model R is the model of random nonresponse. Under Model R, there is a single probability of nonresponse for all units at both times regardless of survey classification. Under Model A, the probability that a unit is missing at time t depends on both the time and the survey classification at the time when the unit responds. Note that if Model A is used for the λ-parameters and the unconstrained model is used for the p_{ij}, then the model is a saturated model which will fit the data exactly. Under Model B, the probability that a unit is missing at time t depends only on the time. Under Model C, the probability that a unit is missing at time t depends only on the unit's survey classification at the time when the unit responds. Under Model D, the probability that a unit is missing at time t depends on both the time and the survey classification at the time when the unit is missing. If Model D is used for the λ-parameters and the unconstrained model is used for the p_{ij}, then the model is a saturated model which will fit the data exactly. Under Model E, the probability that a unit is missing at time t depends only on the unit's survey classification at the time when the unit is missing.

Under Model R, nonresponse is said to be completely at random. Under Models A, B, and C, nonresponse is said to be ignorable nonresponse in that the nonresponse mechanism depends only on the observed data. Nonresponse under Models D and E is nonignorable nonresponse since the nonresponse mechanism depends on the missing data. (See Little and Rubin (1987) for more information on the types of nonresponse.)

In the following two subsections, we describe procedures for fitting the models presented above. The fits of the models can be assessed using either the Pearson X^2 statistic or G^2, the likelihood ratio statistic. Both statistics have asymptotic χ^2 distributions, with degrees of freedom as shown above, given that the model is correct. In the following we use the notation "Model R-U" to denote the pairing of Model R for the λ-parameters and the unconstrained model for the p_{ij}. "Model R-S" will denote the pairing of Model R for the λ-parameters and the symmetric model for the p_{ij}. Similar notation will be used to denote the pairings of Models A, B, C, D, and E for the λ-parameters with one of the two models for the p_{ij}.

3.3   Estimation of the p and λ Parameters Under Models R, A, B, and C

The likelihood functions for the eight models created using one of the two models for the p_{ij} and Model R, A, B, or C for the λ_{tij} factor into two pieces: one piece a function of the p-parameters alone and one a function of the λ-parameters alone. Thus, the MLE's may be found separately for the two sets of parameters. In addition, the p-parameter estimates do not depend on which of these four models is used for the λ-parameters, and the λ-parameter estimates do not depend on which of the two models is used for the p-parameters.

An iterative procedure for obtaining MLE's for the p-parameters under the unconstrained model paired with Model R, A, B, or C for the λ-parameters is given in Chen and Fienberg (1974). The equations for this procedure are provided in Appendix II.

Under the symmetric model for the p-parameters paired with Model R, A, B, or C for the λ-parameters, the factor of the likelihood equation involving only the p_{ij}'s is as follows:

$$\left\{ \prod_{i=1}^{k} p_{ii}^{x_{ii}} \right\} \times \left\{ \prod_{i=1}^{k} \prod_{j=i+1}^{k} p_{ij}^{x_{ij}} \right\} \times \left\{ \prod_{i=2}^{k} \prod_{j=1}^{i-1} p_{ji}^{x_{ij}} \right\}$$

$$\times \left\{ \prod_{i=1}^{k} p_{i\cdot}^{x_{iM}} \right\} \times \left\{ \prod_{j=1}^{k} p_{\cdot j}^{x_{Mj}} \right\}, \tag{1}$$

where a dot in a subscript indicates summation over that subscript. Equation (1) is maximized subject to the constraint that the sum of the p_{ij}'s is one. In general, an iterative procedure is required to obtain the MLE's. Let $x.. = \sum_{i=1}^{K} \sum_{j=1}^{K} x_{ij}$ be the total number of units observed at both times and let $n = x.. + x_{.M} + x_{M.}$ be the total number of units observed in at least one of the two interview times. Then the iterative procedure used in the data analysis reported in Section 4 is as follows:

Iterative Procedure for Estimating Symmetric p_{ij} Under Models R, A, B, and C

1. $p_{ii}^{(0)} = x_{ii}/x..$

$$p_{ij}^{(0)} = (x_{ij} + x_{ji})/2x.. \quad \text{for} \quad i \neq j.$$

2. $p_{ii}^{(v+1)} = \left[x_{ii} + (x_{iM} + x_{Mi}) p_{ii}^{(v)} / p_{i.}^{(v)} \right] / n$

$$p_{ij}^{(v+1)} = \left[(x_{ij} + x_{ji}) + (x_{iM} + x_{Mi}) p_{ij}^{(v)} / p_{i.}^{(v)} + (x_{jM} + x_{Mj}) p_{ij}^{(v)} / p_{j.}^{(v)} \right] / 2n \quad \text{for} \quad i \neq j.$$

Step 2 is repeated for $v = 0, 1, 2, \ldots$ until the parameter estimates converge to the desired degree of accuracy. The initial estimates given in step 1 are merely suggested estimates. Other positive values satisfying the constraint that the p_{ij}'s sum to one may be used.

An iterative procedure for obtaining MLE's for the λ-parameters under Model A and the closed-form estimator for the λ-parameters under Model B are given in Chen and Fienberg (1974). An iterative procedure for obtaining MLE's for the λ-parameters under Model C is given in Stasny (1986). The equations for these procedures are provided in Appendix II.

Under Model R for the λ-parameters, the factor of the likelihood equation involving only λ is as follows:

$$\left\{ \prod_{i=1}^{K} \prod_{j=1}^{K} (1 - 2\lambda)^{x_{ij}} \right\} \times \left\{ \prod_{i=1}^{K} \lambda^{x_{iM}} \right\} \times \left\{ \prod_{j=1}^{K} \lambda^{x_{Mj}} \right\}.$$

The closed-form MLE for λ is

$$\hat{\lambda} = (x_{.M} + x_{M.})/2n.$$

3.4 Estimation of the p and λ Parameters Under Model D

The likelihood functions for the observed data under either Model D-U or Model D-S cannot be factored and all parameter estimates must be obtained simultaneously. An iterative procedure for obtaining MLE's under Model D-U is given in Stasny (1988). The equations for this procedure are provided in Appendix II. Under Model D-S, the likelihood function for the observed data is as follows:

$$\left\{ \prod_{i=1}^{K} p_{ii}^{x_{ii}} \right\} \times \left\{ \prod_{i=1}^{K} \prod_{j=i+1}^{K} p_{ij}^{x_{ij}} \right\} \times \left\{ \prod_{i=2}^{K} \prod_{j=i}^{i-1} p_{ji}^{x_{ij}} \right\} \times \left\{ \prod_{i=1}^{K} \prod_{j=1}^{K} [(1 - \lambda_{1i} - \lambda_{2j})]^{x_{ij}} \right\}$$

$$\times \left\{ \prod_{i=1}^{K} \left[\sum_{j=1}^{K} p_{ij} \lambda_{2j} \right]^{x_{iM}} \right\} \times \left\{ \prod_{j=1}^{K} \left[\sum_{i=1}^{K} p_{ji} \lambda_{1i} \right]^{x_{Mj}} \right\}. \tag{2}$$

Equation (2) is maximized subject to the constraint that the sum of the p_{ij}'s is one. In general, an iterative procedure is required in order to obtain the MLE's. The iterative procedure used in the data analysis reported in Section 4 is as follows:

Iterative Procedure for Estimating Parameters Under Model D-S

1. $p_{ii}^{(0)} = x_{ii}/x_{..}$

   $p_{ij}^{(0)} = (x_{ij} + x_{ji})/2x_{..}$ for $i \neq j$

   $\lambda_{1i}^{(0)} = x_{M.}/n$

   $\lambda_{2j}^{(0)} = x_{.M}/n$.

2. $p_{ii}^{(\nu+1)} = n^{-1} \left\{ x_{ii} + x_{iM} \left[p_{ii}^{(\nu)} \lambda_{2i}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_{2h}^{(\nu)} \right] + x_{Mi} \left[p_{ii}^{(\nu)} \lambda_{1i}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_{1h}^{(\nu)} \right] \right\}$

   $p_{ij}^{(\nu+1)} = (2n)^{-1} \left\{ x_{ij} + x_{ji} + x_{iM} \left[p_{ij}^{(\nu)} \lambda_{2j}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_{2h}^{(\nu)} \right] \right.$

   $\qquad + x_{jM} \left[p_{ij}^{(\nu)} \lambda_{2i}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{jh}^{(\nu)} \lambda_{2h}^{(\nu)} \right] + x_{Mi} \left[p_{ij}^{(\nu)} \lambda_{1j}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_{1h}^{(\nu)} \right]$

   $\qquad \left. + x_{Mj} \left[p_{ij}^{(\nu)} \lambda_{1i}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{jh}^{(\nu)} \lambda_{1h}^{(\nu)} \right] \right\}$ for $i \neq j$

   $\lambda_{1i}^{(\nu+1)} = \sum_{j=1}^{K} \left[x_{Mj} p_{ij}^{(\nu)} \lambda_{1i}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{jh}^{(\nu)} \lambda_{1h}^{(\nu)} \right] \middle/ \sum_{j=1}^{K} \left[x_{ij} / (1 - \lambda_{1i}^{(\nu)} - \lambda_{2j}^{(\nu)}) \right]$

   $\lambda_{2j}^{(\nu+1)} = \sum_{i=1}^{K} \left[x_{iM} p_{ij}^{(\nu)} \lambda_{2j}^{(\nu)} \middle/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_{2h}^{(\nu)} \right] \middle/ \sum_{i=1}^{K} \left[x_{ij} / (1 - \lambda_{1i}^{(\nu)} - \lambda_{2j}^{(\nu)}) \right]$.

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the parameter estimates converge to the desired degree of accuracy. The initial estimates given in step 1 are merely suggested estimates. Other values between zero and one satisfying the constraint that the p_{ij}'s sum to one may be used.

3.5   Estimation of the p and λ Parameters Under Model E

The likelihood functions for the observed data under either Model E-U or Model E-S cannot be factored and all parameter estimates must be obtained simultaneously. An iterative procedure for obtaining MLE's under Model E-U is given in Stasny (1988). The equations for this procedure are provided in Appendix II. Under Model E-S, the likelihood function for the observed data is as follows:

$$\left\{ \prod_{i=1}^{K} p_{ii}^{x_{ii}} \right\} \times \left\{ \prod_{i=1}^{K} \prod_{j=i+1}^{K} p_{ij}^{x_{ij}} \right\} \times \left\{ \prod_{i=2}^{K} \prod_{j=1}^{i-1} p_{ji}^{x_{ij}} \right\} \times \left\{ \prod_{i=1}^{K} \prod_{j=1}^{K} \left[(1 - \lambda_i - \lambda_j) \right]^{x_{ij}} \right\}$$

$$\times \left\{ \prod_{i=1}^{K} \left[\sum_{j=1}^{K} p_{ij} \lambda_j \right]^{x_{iM}} \right\} \times \left\{ \prod_{j=1}^{K} \left[\sum_{i=1}^{K} p_{ji} \lambda_i \right]^{x_{Mj}} \right\}. \tag{3}$$

Equation (3) is maximized subject to the constraint that the sum of the p_{ij}'s is one. In general, an iterative procedure is required in order to obtain the MLE's. The iterative procedure used in the data analysis reported in Section 4 is as follows:

Iterative Procedure for Estimating Parameters Under Model E-S

1. $p_{ii}^{(0)} = x_{ii}/x_{..}$

   $p_{ij}^{(0)} = (x_{ij} + x_{ji})/2x_{..}$ for $i \neq j$

   $\lambda_i^{(0)} = (x_{M.} + x_{.M})/2n.$

2. $p_{ii}^{(\nu+1)} = n^{-1} \left\{ x_{ii} + (x_{iM} + x_{Mi}) \left[p_{ii}^{(\nu)} \lambda_i^{(\nu)} \Big/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_h^{(\nu)} \right] \right\}$

   $p_{ij}^{(\nu+1)} = (2n)^{-1} \left\{ x_{ij} + x_{ji} + (x_{iM} + x_{Mi}) \left[p_{ij}^{(\nu)} \lambda_j^{(\nu)} \Big/ \sum_{h=1}^{K} p_{ih}^{(\nu)} \lambda_h^{(\nu)} \right] \right.$

   $\left. + (x_{jM} + x_{Mj}) \left[p_{ij}^{(\nu)} \lambda_i^{(\nu)} \Big/ \sum_{h=1}^{K} p_{jh}^{(\nu)} \lambda_h^{(\nu)} \right] \right\}$ for $i \neq j$

   $\lambda_i^{(\nu+1)} = \sum_{j=1}^{K} \left[(x_{jM} + x_{Mj}) p_{ji}^{(\nu)} \lambda_i^{(\nu)} \Big/ \sum_{h=1}^{K} p_{jh}^{(\nu)} \lambda_h^{(\nu)} \right]$

   $\Big/ \sum_{j=1}^{K} \left[(x_{ij} + x_{ji})/(1 - \lambda_i^{(\nu)} - \lambda_j^{(\nu)}) \right].$

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the parameter estimates converge to the desired degree of accuracy. The initial estimates given in step 1 are merely suggested estimates. Other values between zero and one satisfying the constraint that the p_{ij}'s sum to one may be used.

4. FITS OF THE MODELS TO NCS DATA

The models described in Section 3 were fit to the NCS data described in Section 2. Recall that the NCS data for each of the years from 1975 to 1978 is summarized both by number of crimes reported in each of the two interviews during the year and by the type of crime reported. Since three survey classifications are used, we have $K = 3$. Standard errors of the parameter estimates were obtained using the observed information matrix.

Table 3a

Estimates of p_{ij} for Flows Among Number-of-Crime Classifications
Under Models R, A, B, and C

		Unconstrained Model			Symmetric Model		
		Second Interview					
		Crime Free	Single Crime	Multiple Crime	Crime Free	Single Crime	Multiple Crime
1975							
First	Crime Free	.666 (.0075)	.098 (.0050)	.029 (.0031)	.666 (.0075)	.102 (.0035)	.032 (.0022)
Interview	Single Crime	.106 (.0051)	.029 (.0031)	.014 (.0023)	.102 (.0035)	.029 (.0031)	.012 (.0015)
	Multiple Crime	.036 (.0032)	.011 (.0021)	.012 (.0021)	.032 (.0022)	.012 (.0015)	.012 (.0021)
1976							
First	Crime Free	.669 (.0076)	.101 (.0052)	.029 (.0033)	.669 (.0076)	.099 (.0036)	.030 (.0022)
Interview	Single Crime	.098 (.0051)	.034 (.0034)	.014 (.0025)	.099 (.0036)	.034 (.0034)	.014 (.0017)
	Multiple Crime	.031 (.0030)	.014 (.0023)	.011 (.0022)	.030 (.0022)	.014 (.0017)	.010 (.0022)
1977							
First	Crime Free	.670 (.0079)	.115 (.0058)	.032 (.0034)	.671 (.0079)	.103 (.0037)	.030 (.0023)
Interview	Single Crime	.092 (.0051)	.026 (.0032)	.016 (.0026)	.103 (.0037)	.026 (.0032)	.016 (.0018)
	Multiple Crime	.028 (.0030)	.016 (.0026)	.006 (.0017)	.030 (.0023)	.016 (.0018)	.006 (.0017)
1978							
First	Crime Free	.671 (.0087)	.097 (.0062)	.027 (.0035)	.671 (.0087)	.105 (.0043)	.027 (.0025)
Interview	Single Crime	.111 (.0061)	.032 (.0040)	.009 (.0022)	.105 (.0043)	.032 (.0040)	.010 (.0017)
	Multiple Crime	.027 (.0034)	.013 (.0027)	.013 (.0026)	.027 (.0025)	.010 (.0017)	.013 (.0026)

Note: Estimated standard errors are given in parentheses.

4.1 Estimates of the p-Parameters Under Models R, A, B, and C

Recall that the p-parameter estimates do not depend on the nonresponse mechanism under Models R, A, B, and C. For the iterative procedures used to estimate the p_{ij} under both the unconstrained and symmetric models, the criterion used for stopping the iteration was that the expected counts in the (i,j) cell of the flow matrix, $n\hat{p}_{ij}$, differed by no more than 0.5 from one step of the iterative procedure to the next. In all cases, convergence occurred rapidly, taking at most six steps. The estimates of the p_{ij} when HH's are classified by numbers of crimes reported are given in Table 3a for both the unconstrained and symmetric models. The estimates of the p_{ij} when HH's are classified by types of crimes reported are given in Table 4a for both the unconstrained and symmetric models.

Table 3b

Estimates of p_{ij} for Flows Among Number-of-Crime Classifications
Under Models D-S

			Symmetric Model		
			Second Interview		
			Crime Free	Single Crime	Multiple Crime
1975		Crime Free	.638 (.0104)	.106 (.0047)	.035 (.0029)
	First	Single Crime	.106 (.0047)	.033 (.0039)	.015 (.0019)
	Interview	Multiple Crime	.035 (.0029)	.015 (.0019)	.016 (.0027)
1976		Crime Free	.645 (.0100)	.100 (.0045)	.034 (.0029)
	First	Single Crime	.100 (.0045)	.037 (.0041)	.017 (.0021)
	Interview	Multiple Crime	.034 (.0029)	.017 (.0021)	.015 (.0029)
1977		Crime Free	.642 (.0109)	.106 (.0054)	.033 (.0032)
	First	Single Crime	.106 (.0054)	.031 (.0043)	.021 (.0023)
	Interview	Multiple Crime	.033 (.0032)	.021 (.0023)	.009 (.0025)
1978		Crime Free	.636 (.0118)	.114 (.0056)	.028 (.0029)
	First	Single Crime	.114 (.0056)	.040 (.0051)	.013 (.0021)
	Interview	Multiple Crime	.028 (.0029)	.013 (.0021)	.015 (.0030)

Note: Estimated standard errors are given in parentheses.

Notice in both Tables 3a and 4a that the flow matrices of estimated probabilities under the unconstrained model for the p_{ij} appear to be fairly symmetric so that the model of symmetry in the flows is suggested as a reasonable model to consider. Also notice that the estimates of the p_{ij} do not appear to change much over the four years. The fits of these two models for the p_{ij} will be considered for each of the four models for nonresponse in Subsection 4.4 below.

Table 3c

Estimates of p_{ij} for Flows Among Number-of-Crime Classifications
Under Models E-U and E-S

		Unconstrained Model			Symmetric Model		
		Second Interview					
		Crime Free	Single Crime	Multiple Crime	Crime Free	Single Crime	Multiple Crime
1975							
First	Crime Free	.639 (.0104)	.102 (.0061)	.031 (.0037)	.639 (.0104)	.106 (.0047)	.035 (.0028)
Interview	Single Crime	.110 (.0061)	.033 (.0039)	.016 (.0026)	.106 (.0047)	.033 (.0039)	.015 (.0019)
	Multiple Crime	.039 (.0039)	.014 (.0025)	.016 (.0027)	.035 (.0028)	.015 (.0019)	.016 (.0027)
1976							
First	Crime Free	.645 (.0100)	.103 (.0063)	.032 (.0041)	.645 (.0100)	.101 (.0045)	.033 (.0029)
Interview	Single Crime	.098 (.0057)	.037 (.0041)	.017 (.0030)	.101 (.0045)	.037 (.0041)	.017 (.0021)
	Multiple Crime	.035 (.0037)	.017 (.0027)	.016 (.0029)	.033 (.0029)	.017 (.0021)	.016 (.0029)
1977							
First	Crime Free	.636 (.0112)	.124 (.0083)	.037 (.0050)	.642 (.0110)	.106 (.0055)	.033 (.0033)
Interview	Single Crime	.094 (.0060)	.031 (.0043)	.021 (.0031)	.106 (.0055)	.030 (.0043)	.020 (.0023)
	Multiple Crime	.029 (.0036)	.020 (.0031)	.008 (.0024)	.033 (.0033)	.020 (.0023)	.008 (.0025)
1978							
First	Crime Free	.639 (.0118)	.106 (.0078)	.029 (.0042)	.637 (.0118)	.112 (.0055)	.028 (.0029)
Interview	Single Crime	.117 (.0070)	.041 (.0051)	.011 (.0026)	.112 (.0055)	.041 (.0051)	.013 (.0021)
	Multiple Crime	.027 (.0037)	.016 (.0032)	.015 (.0030)	.028 (.0029)	.013 (.0021)	.015 (.0030)

Note: Estimated standard errors are given in parentheses.

Table 4a

Estimates of p_{ij} for Flows Among Type-of-Crime Classifications
Under Models R, A, B, and C

		Unconstrained Model			Symmetric Model		
		Second Interview					
		Crime Free	Property Crime	Contact Crime	Crime Free	Property Crime	Contact Crime
1975							
First	Crime Free	.666 (.0075)	.105 (.0053)	.022 (.0026)	.666 (.0075)	.111 (.0037)	.024 (.0018)
Interview	Property Crime	.118 (.0054)	.044 (.0038)	.010 (.0019)	.111 (.0037)	.044 (.0038)	.008 (.0013)
	Contact Crime	.025 (.0026)	.007 (.0016)	.004 (.0012)	.024 (.0018)	.008 (.0013)	.004 (.0012)
1976							
First	Crime Free	.669 (.0076)	.108 (.0055)	.023 (.0028)	.669 (.0021)	.108 (.0011)	.022 (.0010)
Interview	Property Crime	.108 (.0053)	.047 (.0040)	.010 (.0021)	.108 (.0011)	.047 (.0019)	.011 (.0009)
	Contact Crime	.021 (.0025)	.012 (.0021)	.002 (.0011)	.022 (.0010)	.011 (.0009)	.002 (.0012)
1977							
First	Crime Free	.670 (.0079)	.128 (.0061)	.019 (.0026)	.671 (.0078)	.115 (.0039)	.018 (.0018)
Interview	Property Crime	.103 (.0053)	.041 (.0039)	.008 (.0018)	.115 (.0039)	.041 (.0040)	.008 (.0014)
	Contact Crime	.016 (.0025)	.008 (.0021)	.006 (.0018)	.018 (.0018)	.008 (.0014)	.006 (.0017)
1978							
First	Crime Free	.671 (.0087)	.104 (.0064)	.019 (.0031)	.671 (.0088)	.112 (.0044)	.019 (.0021)
Interview	Property Crime	.119 (.0063)	.040 (.0044)	.010 (.0024)	.112 (.0044)	.040 (.0044)	.010 (.0017)
	Contact Crime	.019 (.0029)	.011 (.0025)	.006 (.0020)	.019 (.0021)	.010 (.0017)	.006 (.0020)

Note: Estimated standard errors are given in parentheses.

Table 4b

Estimates of p_{ij} for Flows Among Type-of-Crime Classifications
Under Models D-S

| | | | Symmetric Model | | |
| | | | | Second Interview | |
			Crime Free	Property Crime	Contact Crime
1975					
	First	Crime Free	.635 (.0101)	.118 (.0046)	.026 (.0026)
	Interview	Property Crime	.118 (.0046)	.052 (.0046)	.011 (.0016)
		Contact Crime	.026 (.0026)	.011 (.0016)	.005 (.0016)
1976					
	First	Crime Free	.641 (.0098)	.110 (.0046)	.026 (.0028)
	Interview	Property Crime	.110 (.0046)	.052 (.0048)	.015 (.0021)
		Contact Crime	.026 (.0028)	.015 (.0021)	.004 (.0019)
1977					
	First	Crime Free	.642 (.0104)	.120 (.0052)	.019 (.0024)
	Interview	Property Crime	.120 (.0052)	.050 (.0049)	.011 (.0019)
		Contact Crime	.019 (.0024)	.011 (.0019)	.008 (.0022)
1978					
	First	Crime Free	.636 (.0117)	.121 (.0057)	.020 (.0025)
	Interview	Property Crime	.121 (.0057)	.049 (.0055)	.012 (.0021)
		Contact Crime	.020 (.0025)	.012 (.0021)	.008 (.0025)

Note: Estimated standard errors are given in parentheses.

Table 4c

Estimates of p_{ij} for Flows Among Type-of-Crime Classifications
Under Models E-U and E-S

		Unconstrained Model			Symmetric Model		
		Second Interview					
		Crime Free	Property Crime	Contact Crime	Crime Free	Property Crime	Contact Crime
1975							
First	Crime Free	.636 (.0100)	.111 (.0062)	.024 (.0034)	.636 (.0101)	.117 (.0046)	.026 (.0026)
Interview	Property Crime	.124 (.0063)	.053 (.0047)	.012 (.0023)	.117 (.0046)	.052 (.0047)	.011 (.0016)
	Contact Crime	.027 (.0033)	.009 (.0020)	.005 (.0016)	.026 (.0026)	.011 (.0016)	.005 (.0016)
1976							
First	Crime Free	.641 (.0098)	.110 (.0065)	.028 (.0041)	.641 (.0098)	.110 (.0046)	.026 (.0028)
Interview	Property Crime	.110 (.0059)	.051 (.0048)	.014 (.0028)	.110 (.0046)	.052 (.0048)	.015 (.0021)
	Contact Crime	.024 (.0033)	.016 (.0028)	.005 (.0019)	.026 (.0028)	.015 (.0021)	.005 (.0019)
1977							
First	Crime Free	.636 (.0108)	.138 (.0076)	.023 (.0035)	.641 (.0105)	.121 (.0051)	.019 (.0024)
Interview	Property Crime	.107 (.0060)	.050 (.0048)	.010 (.0022)	.121 (.0051)	.049 (.0048)	.011 (.0018)
	Contact Crime	.015 (.0028)	.011 (.0027)	.009 (.0023)	.019 (.0024)	.011 (.0018)	.009 (.0022)
1978							
First	Crime Free	.641 (.0117)	.111 (.0078)	.022 (.0040)	.640 (.0117)	.118 (.0056)	.021 (.0026)
Interview	Property Crime	.124 (.0071)	.048 (.0055)	.012 (.0029)	.118 (.0056)	.048 (.0054)	.013 (.0021)
	Contact Crime	.020 (.0033)	.014 (.0031)	.009 (.0025)	.021 (.0026)	.013 (.0021)	.008 (.0025)

Note: Estimated standard errors are given in parentheses.

4.2   Estimates of the λ-Parameters Under Models R, A, B, and C

Recall that the λ-parameter estimates under Models R, A, B, and C are the same regardless of whether the unconstrained or symmetric model is used for the p-parameters. For the iterative procedures used to estimate the λ-parameters under Models A and C, the convergence criterion used was that estimates of the λ-parameters differed by no more than .0005 from one step to the next. Convergence took between 41 and 4150 steps when it occurred in fewer than 10,000 steps after using the initial parameter estimates suggested in Appendix II. The factors of the likelihood for the observed data involving only the λ-parameters were, in some cases, not well behaved. This is particularly true for the likelihoods for the 1978 data under both Models A and C. In such cases, a grid search was used to locate appropriate starting points for the iterative procedures. A rough grid search was also used in all cases to verify that, when the iterative procedure converged, it appeared to have converged to a global rather than a local maximum.

The estimates of the λ-parameters under both the number-of-crimes and type-of-crime classifications for Models R, A, B, and C are given in Tables 5, 6, 7, and 8 respectively.

Notice that under Models R and B the estimates of the λ-parameters are the same for both the number-of-crimes and type-of-crime classifications because the probability of being a nonrespondent under those two models does not depend on survey classification. Under Models A and C, the λ-parameter estimates corresponding to the crime-free classification are the same, within rounding error, for both the number-of-crimes and type-of-crime classifications since crime-free HH's are the same under both classifications. Also notice that, under Models A and C, the λ-parameter estimates, the estimated probabilities of being a nonrespondent, generally increase as the number of victimizations or the seriousness of the crime increases.

Table 5
Estimates of λ Under Model R

	Number-of-Crimes or Type-of-Crime Classification of Data
	$\hat{\lambda}$
1975	.224 (.0035)
1976	.232 (.0035)
1977	.237 (.0036)
1978	.250 (.0040)

Note: Estimated standard errors are given in parentheses.

Table 6

Estimates of λ_{1j} and λ_{2i} Under Model A

	Number-of-Crimes Classification of Data						Type-of-Crime Classification of Data					
	$\hat{\lambda}_{11}$	$\hat{\lambda}_{12}$	$\hat{\lambda}_{13}$	$\hat{\lambda}_{21}$	$\hat{\lambda}_{22}$	$\hat{\lambda}_{23}$	$\hat{\lambda}_{11}$	$\hat{\lambda}_{12}$	$\hat{\lambda}_{13}$	$\hat{\lambda}_{21}$	$\hat{\lambda}_{22}$	$\hat{\lambda}_{23}$
1975	.208	.272	.327	.221	.234	.275	.208	.280	.322	.220	.246	.246
	(.0062)	(.0159)	(.0261)	(.0064)	(.0147)	(.0242)	(.0062)	(.0151)	(.0321)	(.0064)	(.0139)	(.0303)
1976	.206*	.261*	.397*	.236*	.254*	.267*	.206	.278	.381	.235	.253	.285
	(.0063)	(.0152)	(.0268)	(.0066)	(.0153)	(.0248)	(.0063)	(.0146)	(.0327)	(.0066)	(.0144)	(.0319)
1977	.192	.263	.309	.258	.281	.326	.192	.275	.267	.258	.269	.417
	(.0064)	(.0152)	(.0265)	(.0070)	(.0171)	(.0285)	(.0064)	(.0144)	(.0327)	(.0069)	(.0159)	(.0369)
1978	.207*	.316*	.302*	.269*	.280*	.321*	.207*	.305*	.343*	.269*	.280*	.334*
	(.0072)	(.0182)	(.0308)	(.0079)	(.0176)	(.0300)	(.0072)	(.0174)	(.0364)	(.0079)	(.0166)	(.0362)

Note: * Indicates cases in which the likelihood function is not well behaved.
Estimated standard errors are given in parentheses.

Table 7

Estimates of λ_1 and λ_2 Under Model B

	Number-of-Crimes or Type-of-Crime Classification of Data	
	$\hat{\lambda}_1$	$\hat{\lambda}_2$
1975	.223	.226
	(.0058)	(.0058)
1976	.225	.240
	(.0059)	(.0060)
1977	.209	.264
	(.0059)	(.0064)
1978	.227	.273
	(.0067)	(.0071)

Note: Estimated standard errors are given in parentheses.

Table 8

Estimates of λ_i Under Model C

	Number-of-Crimes Classification of Data			Type-of-Crime Classification of Data		
	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$
1975	.214	.252	.300	.214	.262	.284
	(.0039)	(.0118)	(.0199)	(.0039)	(.0109)	(.0262)
1976	.221	.257	.330	.221	.266	.333
	(.0040)	(.0116)	(.0210)	(.0040)	(.0109)	(.0289)
1977	.225	.271	.317	.225*	.273*	.339*
	(.0041)	(.0126)	(.0235)	(.0041)	(.0115)	(.0286)
1978	.237*	.297*	.312*	.237*	.292*	.339*
	(.0046)	(.0139)	(.0236)	(.0046)	(.0130)	(.0299)

Note: * Indicates cases in which the likelihood function is not well behaved.
Estimated standard errors are given in parentheses.

4.3   Parameter Estimates Under Models D and E

Models D and E are more difficult to fit than Models R, A, B, and C because all parameters under Models D and E must be estimated simultaneously. For all sets of the NCS data, the likelihood functions under Models D and E were not well behaved and grid searches over the possible values of the λ-parameters were required to locate suitable starting points for the iterative procedure. Since a grid search over the six λ-parameters under Model D was extremely time-consuming, parameter estimates were obtained under Model D-S but not under Model D-U. Estimates of the p-parameters under Model D-S are given in Table 3b for the number-of-crimes classification and in Table 4b for the type-of-crime classification. The λ-parameter estimates under Model D-S are given in Table 9 for both types of classifications. Estimates of the p-parameters under Models E-U and E-S are given in Table 3c for the number-of-crimes classification and in Table 4c for the type-of-crime classification. The λ-parameter estimates under Models E-U and E-S are given in Table 10 for both types of classifications.

Notice that under Models D and E the estimates of p_{11}, the probability of remaining in the crime-free classification, are somewhat smaller that the corresponding estimates under Models R, A, B, and C; the estimates of the remaining p-parameters under Models D and E are somewhat larger than the corresponding estimates under Models R, A, B, and C. Under both Models D and E, the λ-parameter estimates, the estimated probabilities of being a nonrespondent, generally increase as the number of victimizations or the seriousness of the crime increases. In the cases where the estimates decrease as the number of victimizations or the seriousness of the crime increases (in the 1978 data under Model D-S and in the 1978 number-of-crimes data under Model E-S), the decreases are small and within the estimated standard error of the estimates.

Table 9

Estimates of λ_{1i} and λ_{2j} Under Model D-S

	Number-of-Crimes Classification of Data						Type-of-Crime Classification of Data					
	$\hat{\lambda}_{11}$	$\hat{\lambda}_{12}$	$\hat{\lambda}_{13}$	$\hat{\lambda}_{21}$	$\hat{\lambda}_{22}$	$\hat{\lambda}_{23}$	$\hat{\lambda}_{11}$	$\hat{\lambda}_{12}$	$\hat{\lambda}_{13}$	$\hat{\lambda}_{21}$	$\hat{\lambda}_{22}$	$\hat{\lambda}_{23}$
1975	.210	.246	.319	.194	.321	.387	.208	.264	.319	.192	.339	.372
	(.0085)	(.0303)	(.0368)	(.0085)	(.0282)	(.0362)	(.0084)	(.0249)	(.0523)	(.0085)	(.0235)	(.0507)
1976	.204	.276	.339	.217	.273	.444	.203	.280	.383	.215	.297	.453
	(.0083)	(.0274)	(.0344)	(.0084)	(.0291)	(.0331)	(.0083)	(.0244)	(.0443)	(.0084)	(.0255)	(.0416)
1977	.175	.307	.380	.249	.298	.374	.175	.304	.438	.248	.315	.341
	(.0086)	(.0301)	(.0403)	(.0089)	(.0326)	(.0439)	(.0086)	(.0243)	(.0424)	(.0089)	(.0259)	(.0491)
1978	.211	.278	.290	.236	.413	.384	.211	.276	.293	.236	.411	.391
	(.0094)	(.0282)	(.0433)	(.0099)	(.0261)	(.0443)	(.0094)	(.0264)	(.0563)	(.0098)	(.0246)	(.0567)

Note: Estimated standard errors are given in parentheses.

Table 10

Estimates of λ_i Under Model E

	Number-of-Crimes Classification of Data			Type-of-Crime Classification of Data		
	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$
	Unconstrained p_{ij}					
1975	.202 (.0060)	.285 (.0235)	.348 (.0262)	.201 (.0058)	.302 (.0180)	.336 (.0418)
1976	.211 (.0057)	.275 (.0226)	.387 (.0232)	.209 (.0056)	.286 (.0193)	.419 (.0327)
1977	.210 (.0063)	.315 (.0259)	.372 (.0351)	.209 (.0061)	.318 (.0183)	.394 (.0295)
1978	.224 (.0065)	.340 (.0208)	.342 (.0296)	.225 (.0065)	.326 (.0203)	.385 (.0333)
	Symmetric p_{ij}					
1975	.202 (.0060)	.285 (.0235)	.351 (.0258)	.201 (.0059)	.301 (.0180)	.341 (.0408)
1976	.211 (.0057)	.274 (.0223)	.389 (.0229)	.209 (.0056)	.287 (.0191)	.418 (.0327)
1977	.213 (.0061)	.301 (.0267)	.376 (.0339)	.213 (.0060)	.309 (.0190)	.391 (.0302)
1978	.224 (.0065)	.343 (.0204)	.338 (.0298)	.225 (.0065)	.329 (.0199)	.379 (.0339)

Note: Estimated standard errors are given in parentheses.

4.4 Fits of the Models

Table 11 shows the X^2 and G^2 values and the associated degrees of freedom for all twelve models (including Model D-U which must fit the data exactly) and both types of survey classifications. Note that the models were fit as an illustration of the methods developed here and we have ignored the complex survey design. Although clusters are not a problem in our subsample of the NCS data, in a more complete analysis we would prefer to fit the models separately to data from different strata and then combine the strata estimates to obtain estimates for the entire population.

Clearly, neither Model R, the model of random nonresponse, nor Model B, under which the probability of nonresponse depends only on time, fits the data well for either the unconstrained or symmetric models for the p_{ij}.

Models C-U and C-S fit the 1975 data fairly well and give reasonable fits to the 1976 data. Since Model C-S fits the data reasonably well and is a more parsimonious model, we prefer it over Model C-U. Under Model C, the probability of nonresponse depends only on the victimization classification at the interview in which the HH responded, not on the time. Thus, Model C is the model of symmetry in the nonresponse probabilities for the two interview periods. When Model C is paired with the symmetric model for the p-parameters, we obtain symmetric expected cell counts for the observed flow data. Notice in the observed data shown in Appendix I, that in 1977 and 1978 there is much more nonresponse at the second interview time than at the first interview time. This difference in nonresponse rates is the reason for the lack of fit of Model C to the 1977 and 1978 data.

Table 11

Fits of the Models

| | Number-of-Crimes Classification of Data | | | | Type-of-Crime Classification of Data | | | |
| | Unconstrained p_{ij} | | Symmetric p_{ij} | | Unconstrained p_{ij} | | Symmetric p_{ij} | |
	X^2	G^2	X^2	G^2	X^2	G^2	X^2	G^2
Model R	(d.f. = 5)		(d.f. = 8)		(d.f. = 5)		(d.f. = 8)	
1975	42.7	41.2	45.9	45.6	38.2	36.9	42.0	41.5
1976	70.2	67.1	69.7	67.7	57.7	55.9	58.3	56.4
1977	74.2	75.2	83.9	85.3	85.4	84.8	94.8	95.3
1978	61.7	62.7	64.9	66.3	63.2	64.1	65.5	66.8
Model A	(d.f. = 0)		(d.f. = 3)		(d.f. = 0)		(d.f. = 3)	
1975	0.0	0.0	4.4	4.4	0.0	0.0	4.6	4.6
1976	0.0	0.0	0.6	0.6	0.0	0.0	0.5	0.5
1977	0.0	0.0	10.1	10.1	0.0	0.0	10.5	10.5
1978	0.0	0.0	3.7	3.7	0.0	0.0	2.7	2.7
Model B	(d.f. = 4)		(d.f. = 7)		(d.f. = 4)		(d.f. = 7)	
1975	42.7	41.1	45.9	45.5	38.2	36.9	42.0	41.5
1976	69.1	64.5	68.5	65.1	56.2	53.3	56.9	53.8
1977	47.1	45.4	58.7	55.5	57.0	54.9	68.4	65.4
1978	47.6	46.0	50.1	49.6	49.1	47.4	50.7	50.1
Model C	(d.f. = 3)		(d.f. = 6)		(d.f. = 3)		(d.f. = 6)	
1975	6.9	6.9	11.3	11.3	7.4	7.4	12.0	12.0
1976	21.2	21.3	21.8	21.9	15.1	15.1	15.6	15.6
1977	38.1	38.3	48.2	48.4	45.6	45.7	56.0	56.3
1978	31.1	31.1	34.7	34.8	29.9	30.0	32.6	32.7
Model D	(d.f. = 0)		(d.f. = 3)		(d.f. = 0)		(d.f. = 3)	
1975	0.0	0.0	5.0	5.0	0.0	0.0	5.6	5.6
1976	0.0	0.0	15.3	15.3	0.0	0.0	11.6	11.6
1977	0.0	0.0	11.5	11.5	0.0	0.0	18.0	18.0
1978	0.0	0.0	10.2	10.2	0.0	0.0	9.9	9.8
Model E	(d.f. = 3)		(d.f. = 6)		(d.f. = 3)		(d.f. = 6)	
1975	7.0	7.0	11.3	11.3	7.3	7.3	12.0	12.0
1976	21.0	21.1	21.8	21.9	14.8	14.9	15.6	15.6
1977	33.0	33.0	48.2	48.4	39.5	39.5	56.0	56.3
1978	32.0	32.1	34.6	34.8	30.9	31.0	32.6	32.7

Note: $\chi^2_{.99}(3) = 11.34$, $\chi^2_{.99}(4) = 13.28$, $\chi^2_{.99}(5) = 15.09$, $\chi^2_{.99}(6) = 16.81$, $\chi^2_{.99}(7) = 18.48$, and $\chi^2_{.99}(8) = 20.09$.

The fits of Models E-U and E-S are quite similar to those of Models C-U and C-S respectively. This is not surprising since the interpretations of the model are quite similar. Under Model C nonresponse depends on the survey classification when the HH responds while under Model E it depends on the survey classification when the HH does not respond. Since the fits of these two models are similar, we cannot choose between the two models using the data alone. Logically, Model E seems more realistic since we might expect nonresponse to depend on the current victimization status. Since the two models provide similar fits to the data, it may be that the victimization status at the time when the HH responds is generally a good indicator for the victimization status when the HH does not respond. If that is the case, we would prefer to use Model C since it is easier to fit than Model E.

Model A-S, under which nonresponse depends on both the time and on the victimization status when the HH responds fits the 1975, 1976, and 1978 data very well and gives a reasonable fit to the 1977 data. The fits of Model D-S are similar to those of Model A-S with the exception of the 1976 data which is fit much better by Model A-S. Again we cannot choose between Model A and D based on the data alone. (Models A-U and D-U fit the data exactly.) In general, we are quite pleased with the fits of Model A-S to both the number-of-crimes and type-of-crime data from all four years. Since Model A provides a reasonable fit to all the data, we conclude that nonresponse in the NCS does depend on victimization status.

Notice that, in most cases, the fits of the models as measured by X^2 and G^2 do not change much when the symmetric p_{ij} model is used rather than the unconstrained p_{ij} model. Since we gain 3 degrees of freedom going to the more parsimonious, symmetric model for the p_{ij}, we prefer this model to the unconstrained model for the p_{ij}. This choice of the symmetric model for the flow probabilities indicates that there is a certain amount of stability in victimizations reported in the first and second halves of the year in the NCS. This stability comes from the fact that symmetry in the underlying flow probabilities implies equality of marginal totals. Thus, the numbers of HH's having no crimes, one crime, or two or more crimes remain about the same from the first interview of a year to the second year. Similarly, the numbers of HH's having no crimes, a property crime, or a contact crime remain about the same from the first interview of a year to the second year.

5.   CONCLUSIONS AND FUTURE WORK

We have seen that the model of symmetry in the matrices of flows among victimization classifications paired with a model under which nonresponse depends on both time and victimization status, provides a good fit to data summaries from the NCS. The same model fits the data when classification of HH's is by number of crimes reported or by type of crime reported.

The work described here is, of course, only an initial attempt to explore nonresponse and flows among victimization classifications in NCS data. For example, we noticed that the estimated symmetric probabilities of flows among the classifications did not appear to change much over the four-year period from 1975 to 1978 but the estimated probabilities of nonresponse did appear to change over this period. One might wish to fit a model to the NCS data which has constant flow probabilities but allows the nonresponse probabilities to change over time. If the nonresponse probabilities do actually change over time, not just from year to year but also from interview period to interview period, then it would be important to try to discover why these probabilities are changing.

In the work presented here, all missing data were treated the same. In fact, data may be missing because a HU rotated out of the sample, because a HH moved into or out of the sampled HU, because no one was at home, because the HH refused to respond, or for some other reason. It may be reasonable to assume that data missing because a HU rotated out of the sample is missing at random, but that other types of nonresponse are not missing at random. Stasny (1988) presents models that allow for different types of nonresponse which could be used with the models of symmetry in flows presented here. In addition, the models here do not allow for HH's which are missing at both interview periods. Since there are, of course, such HH's, one may wish to explore Markov-chain model such as those given in Stasny (1987) which do handle nonresponse at both times.

Most importantly, one may want to consider more natural summaries of the data than were used here. The data used here were summarized by first and second interview for the year. A more meaningful summary would be, say, by month or quarter of the year. If such summaries were used, then the complex nature of the interview schedule for the NCS would have to be considered and accounted for in the models. For example, the response status for a HH would be the same for the six-month reporting period covered at any one interview time. The development of models taking this into account is an important area for future work.

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APPENDIX I

The Observed Data

			Classification by Number of Victimizations			
			Second Interview			
			Crime Free	Single Crime	Multiple Crime	Missing
1975						
	First	Crime Free	1963	256	67	901
	Interview	Single Crime	306	73	31	179
		Multiple Crime	95	26	24	83
		Missing	866	193	91	
1976						
	First	Crime Free	1884	257	53	951
	Interview	Single Crime	266	84	24	186
		Multiple Crime	82	34	18	75
		Missing	831	197	106	
1977						
	First	Crime Free	1742	260	66	994
	Interview	Single Crime	228	56	31	177
		Multiple Crime	63	31	10	76
		Missing	716	194	79	
1978						
	First	Crime Free	1370	157	45	831
	Interview	Single Crime	222	50	14	165
		Multiple Crime	50	18	19	66
		Missing	651	174	57	

			Classification by Type of Crime			
			Second Interview			
			Crime Free	Property Crime	Contact Crime	Missing
1975						
	First	Crime Free	1963	271	52	901
	Interview	Property Crime	331	107	22	217
		Contact Crime	70	17	8	45
		Missing	866	225	59	
1976						
	First	Crime Free	1884	266	44	951
	Interview	Property Crime	295	111	19	211
		Contact Crime	53	26	4	50
		Missing	831	235	68	
1977						
	First	Crime Free	1742	283	43	994
	Interview	Property Crime	262	89	18	194
		Contact Crime	29	12	9	59
		Missing	716	231	42	
1978						
	First	Crime Free	1370	173	29	831
	Interview	Property Crime	238	64	14	184
		Contact Crime	34	15	8	47
		Missing	651	184	47	

APPENDIX II: Procedures for Obtaining MLE's of the p and λ Parameters

Note that $x.. = \sum_{i=1}^{K} \sum_{j=1}^{K} x_{ij}$ is the total number of units responding at both times and $n = x.. + x._M + x_M.$ is the total sample size. The starting values given below for the iterative procedures are merely suggested values. Other positive values summing to one may be used as initial values for the p-parameter estimates, and other values between zero and one may be used as initial values for the λ-parameter estimates.

MLE's for Unconstrained p_{ij}'s Under Models R, A, B, and C

1. $p_{ij}^{(0)} = x_{ij}/x..$

2. $p_{ij}^{(\nu+1)} = \left[x_{ij} + x_{iM} p_{ij}^{(\nu)} / p_{i.}^{(\nu)} + x_{Mj} p_{ij}^{(\nu)} / p._{j}^{(\nu)} \right]/n.$

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the p_{ij} parameter estimates converge to a desired degree of accuracy.

MLE's for λ's Under Model A

1. $\lambda_{1j}^{(0)} = x_{M.}/n$ and $\lambda_{2i}^{(0)} = x._M/n.$

2. a) $\lambda_{1j}^{(\nu+1)} = x_{Mj} \Bigg/ \sum_{i=1}^{K} \left[x_{ij}/(1 - \lambda_{1j}^{(\nu)} - \lambda_{2i}^{(\nu)}) \right]$

   b) $\lambda_{2i}^{(\nu+1)} = x_{iM} \Bigg/ \sum_{j=1}^{K} \left[x_{ij}/(1 - \lambda_{1j}^{(\nu)} - \lambda_{2i}^{(\nu)}) \right].$

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the λ-parameter estimates converge to the desired degree of accuracy. If $x_{hM} > \sum_{j=1}^{K} x_{hj}$ or $x_{Mh} > \sum_{i=1}^{K} x_{ih}$ for some h, so that of all units responding in a particular survey classification at one interview time more did not respond at the other interview time than did respond, then the corresponding parameter estimates will, at some step, fall outside of the 0 to 1 range and alternate formulas must be used in place of those given above (see Chen and Fienberg 1974). If for some j $x_{Mj} > \sum_{i=1}^{K} x_{ij}$, then for that j, step 2a) given above is replaced by

$$\lambda_{1j}^{(\nu+1)} = 1 - \lambda_{2h}^{(\nu)} - \left(\lambda_{1j}^{(\nu)} / x_{Mj} \right) \left\{ \sum_{i=1}^{K} \left[x_{ij}/(1 - \lambda_{1j}^{(\nu)} - \lambda_{2i}^{(\nu)}) \right] \right\} (1 - \lambda_{1j}^{(\nu)} - \lambda_{2h}^{(\nu)}),$$

where h is chosen at each step of the iteration so that $\lambda_{2h}^{(\nu)} \geq \lambda_{2i}^{(\nu)}$ for all $i = 1, 2, \ldots K.$ If for some i $x_{iM} > \sum_{j=1}^{K} x_{ij}$, then for that i, step 2b) given above is replaced by

$$\lambda_{2i}^{(\nu+1)} = 1 - \lambda_{1h}^{(\nu)} - \left(\lambda_{2i}^{(\nu)} / x_{iM} \right) \left\{ \sum_{j=1}^{K} \left[x_{ij}/(1 - \lambda_{1j}^{(\nu)} - \lambda_{2i}^{(\nu)}) \right] \right\} (1 - \lambda_{1h}^{(\nu)} - \lambda_{2i}^{(\nu)}),$$

where h is chosen at each step of the iteration so that $\lambda_{1h}^{(\nu)} \geq \lambda_{1j}^{(\nu)}$ for all $j = 1, 2, \ldots K.$

MLE's for λ's Under Model B

$$\hat{\lambda}_1 = x_{M\cdot}/n \quad \text{and} \quad \hat{\lambda}_2 = x_{\cdot M}/n.$$

MLE's for λ's Under Model C

1. $\lambda_i^{(0)} = (x_{iM} + x_{Mi})/2n.$

2. $\lambda_i^{(\nu+1)} = (x_{iM} + x_{Mi})\Big/\Big\{ \sum_{j=1}^{K} \big[(x_{ij} + x_{ji})/(1 - \lambda_i^{(\nu)} - \lambda_j^{(\nu)}) \big] \Big\}.$

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the λ-parameter estimates converge to the desired degree of accuracy. If $x_{Mi} + x_{iM} > \sum_{j=1}^{K} (x_{ij} + x_{ji})$ for some i, then as for Model A an alternate formula must be used in place of step 2 above. In such cases, step 2 is replaced by

$$\lambda_i^{(\nu+1)} = 1 - \lambda_h^{(\nu)} - \big[\lambda_i^{(\nu)}/(x_{iM} + x_{Mi}) \big]$$

$$\Big\{ \sum_{j=1}^{K} \big[(x_{ij} + x_{ji})/(1 - \lambda_i^{(\nu)} - \lambda_j^{(\nu)}) \big] \Big\} (1 - \lambda_h^{(\nu)} - \lambda_i^{(\nu)}),$$

where h is chosen at each step of the iteration so that $\lambda_h^{(\nu)} \geq \lambda_j^{(\nu)}$ for all $j = 1, 2, \ldots K$.

MLE's for Parameters Under Model D-U

1. $p_{ij}^{(0)} = x_{ij}/x_{\cdot\cdot}, \quad \lambda_{1i}^{(0)} = x_{M\cdot}/n, \quad \text{and} \quad \lambda_{2j}^{(0)} = x_{\cdot M}/n.$

2. $p_{ij}^{(\nu+1)} = n^{-1}\Big\{ x_{ij} + x_{iM}\Big[p_{ij}^{(\nu)}\lambda_{2j}^{(\nu)}\Big/ \sum_{h=1}^{K} p_{ih}^{(\nu)}\lambda_{2h}^{(\nu)} \Big] + x_{Mj}\Big[p_{ij}^{(\nu)}\lambda_{1i}^{(\nu)}\Big/ \sum_{h=1}^{K} p_{hj}^{(\nu)}\lambda_{1h}^{(\nu)} \Big] \Big\}$

$$\lambda_{1i}^{(\nu+1)} = \sum_{j=1}^{K} \Big[x_{Mj}p_{ij}^{(\nu)}\lambda_{1i}^{(\nu)}\Big/ \sum_{h=1}^{K} p_{hj}^{(\nu)}\lambda_{1h}^{(\nu)} \Big]\Big/ \sum_{j=1}^{K} \big[x_{ij}/(1 - \lambda_{1i}^{(\nu)} - \lambda_{2j}^{(\nu)}) \big]$$

$$\lambda_{2j}^{(\nu+1)} = \sum_{i=1}^{K} \Big[x_{iM}p_{ij}^{(\nu)}\lambda_{2j}^{(\nu)}\Big/ \sum_{h=1}^{K} p_{ih}^{(\nu)}\lambda_{2h}^{(\nu)} \Big]\Big/ \sum_{i=1}^{K} \big[x_{ij}/(1 - \lambda_{1i}^{(\nu)} - \lambda_{2j}^{(\nu)}) \big].$$

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the λ-parameter estimates converge to the desired degree of accuracy.

MLE's for Parameters Under Model E-U

1. $p_{ij}^{(0)} = x_{ij}/x_{..}$ and $\lambda_i^{(0)} = (x_{M\cdot} + x_{\cdot M})/2n$.

2. $p_{ij}^{(\nu+1)} = n^{-1}\left\{ x_{ij} + x_{iM}\left[p_{ij}^{(\nu)}\lambda_j^{(\nu)} \middle/ \sum_{h=1}^{K} p_{ih}^{(\nu)}\lambda_h^{(\nu)} \right] + x_{Mj}\left[p_{ij}^{(\nu)}\lambda_i^{(\nu)} \middle/ \sum_{h=1}^{K} p_{hj}^{(\nu)}\lambda_h^{(\nu)} \right] \right\}$

$$\lambda_i^{(\nu+1)} = \left\{ \sum_{j=1}^{K} x_{jM}\left[p_{ji}^{(\nu)}\lambda_i^{(\nu)} \middle/ \sum_{h=1}^{K} p_{jh}^{(\nu)}\lambda_h^{(\nu)} \right] + x_{Mj}\left[p_{ij}^{(\nu)}\lambda_i^{(\nu)} \middle/ \sum_{h=1}^{K} p_{hj}^{(\nu)}\lambda_h^{(\nu)} \right] \right\}$$

$$\times \left\{ \sum_{j=1}^{K} (x_{ij} + x_{ji}) \middle/ (1 - \lambda_i^{(\nu)} - \lambda_j^{(\nu)}) \right\}^{-1}.$$

Step 2 is repeated for $\nu = 0, 1, 2, \ldots$ until the λ-parameter estimates converge to the desired degree of accuracy.

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