Behavior Genetics, Vol. 24, No. 5, 1994

A Simple Method for Censored Age-of-Onset Data Subject to Recall Bias: Mothers' Reports of Age of Puberty in Male Twins

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Received 10 Nov. 1993—Final 12 May 1994

Genetic analysis of variation in age of onset of development milestones or psychopathological behaviors has been little researched, owing largely to the computational difficulty of dealing with "censored" observations. Censored observations arise when the only information on individuals is that they have reached a particular age but without onset having occurred. This paper shows how models can be simply fitted to such data using programs that can perform genetic analysis of categorical data by maximum likelihood. The method is illustrated using the program Mx with data on maternal report of the onset of puberty in twin sons from the Virginia Twin Study of Adolescent Behavioral Development. Frequently, data on age of onset is collected by retrospective recall. This can pose a variety of measurement problems. Suggestions are made for models that account for some of these problems or are robust to their presence. Substantial evidence for "telescoping" of onset dates is found for the puberty data. If left unaccounted for, these effects can artifactually inflate estimates of common environment effects.

KEY WORDS: Age of onset; survival analysis; puberty; retrospective recall; recall bias.

INTRODUCTION

Data on twins that have been measured on some variable recorded on an ordinal scale of measurement are common. A crosstabulation of the scores of twin 1 against twin 2 for all twin pairs gives a simple table of frequencies with ordered margins that can be easily analyzed using programs such as Mx (Neale, 1991). A variety of such ordinal variables can be tackled, such as those that refer to increasing frequency of some behavior or event (e.g., never, sometimes, often), increasing strength and direction of some attitude (e.g., strongly disagree, disagree,..., strongly agree), and those based on the direct categorization of some continuous scale, such that the categories correspond to particular ranges of scores or intervals on the scale. One such continuous scale is age or time. This suggests that these familiar models for ordinal data might have some scope for analyzing data on the age at onset of developmental milestones or psychopathological behaviors, a form of twin data that, unless it has been of particularly simple form, has previously been analyzed only using specialist software.

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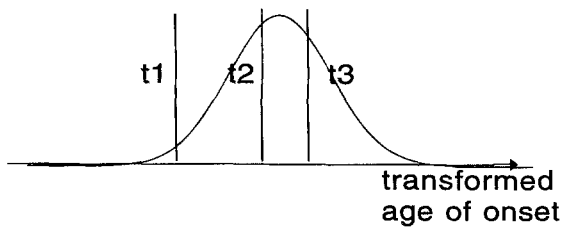

Fig. 1. Age-of-onset intervals and thresholds on a distribution.

This paper shows that this is indeed the case, illustrating how the multigroup approach commonly used for tackling missing data problems in packages for structural equation modeling (Allison, 1987; Muthen *et al.*, 1987; Dunn *et al.*, 1993) can be adapted for use with right (and left) censored data, including censored survival data.

Where ages of onset have been measured continuously and have been observed for all subjects, then a straightforward approach to their analysis has been by transforming them to approximate normality, say by taking logs, and then proceeding in the usual structural equation model fashion. Where the ages of onset are measured only to intervals of time (grouped) but all subjects have a recorded interval of onset, then again, analysis is straightforward, using the crosstabulated ordinal data approach without modification. These models estimate cutpoints or thresholds along the dimension of some latent variable, and as shown in Fig. 1, the proportion of the distribution falling between the thresholds is the expected proportion of subjects experiencing onset within that interval. The thresholds represent locations on a transformed dimension of age, one in which ages of onset are of some assumed distributional form, usually normal. However, that transformation is extremely flexible, because the thresholds, although ordered, are otherwise unconstrained parameters. This gives the ordinal model some advantage over the more parametrically constrained model for continuous data, most obviously where no good normalizing transformation of the age-at-onset data can be found. However, both approaches have been severely restricted by their inability to deal with censored observations, that is, subjects who are part of the sample but who have not yet been observed as experiencing onset.

It was largely to tackle such censored observations that special statistical techniques were developed for survival analysis. These models are constructed, not around the age-of-onset distribution itself, but around the hazard function, the ratio of the density function of the age-of-onset distribution to one minus the cumulative distribution of ages at onset. Developments of these models for twin data have been made (e.g., Hougaard, 1986; Mack *et al.*, 1990; Pickles *et al.*, 1994) but these involve considerable statistical complexity and specialist programming. Most early applications of survival analysis and a number of their recent applications to twin data (e.g., Meyer *et al.*, 1991) have assumed parametric hazard functions. Although these parametric models may have some basis in plausible biological mechanisms, they obscured the link between survival data and more ordinary ordinal data. More recently, with an increased use of nonparametric hazard functions, notably the Cox (1972) proportional hazards model and the piecewise constant or exponential (Breslow, 1974), this simple link has been more widely recognized (e.g., Aitkin *et al.*, 1989). In the absence of covariates, fitting an ordinal model with unconstrained thresholds to age-at-onset data corresponds to the fitting of a piecewise constant discrete time survival mode but in a different parameter space. In the hazard model the survivor function for the probability of surviving into the jth age interval is given by $\Pi_{k=1}^{j-1}(1-h_k)$, where each h_k is a parameter for the hazard in the kth interval (Aitkin *et al.*, p. 312). If $\Phi(.)$ is the cumulative distribution function on the transformed age scale of the ordinal model with threshold parameters t_k, then the corresponding survival probability is $1\text{-}\Phi(t_{j-1})$, and hazard $[\Phi(t_k)-\Phi(t_{k-1})]/[1\text{-}\Phi(t_{k-1})]$. In extending the ordinal model to deal with censored data, we provide a powerful approach with strong links to the mainstream survival analysis literature and one that is straightforward to implement.

CENSORED SURVIVAL DATA FROM TWINS OF THE SAME AGE

To appreciate our approach to analyzing age-of-onset data in twins, we first consider the simplest situation where all twins are observed at the same age, then generalize the approach to situations where twins are observed at different ages. This extension is achieved through grouping the twins such that each group is an example of the simplest "same-age" situation.

Consider a prospective study in which data were collected annually on the birthdays of each twin pair and onset recorded as having occurred or not in the previous year. The simplest situation in which censored observations arise is where data collection has extended only as far as, say, their 16th birthday. Any subject with no recorded onset would contribute a censored observation. However, on the assumption that all individuals in the population are and remain at risk of the event, an assumption that is routinely made in most areas of study, e.g., cancer research, we know that the onset for such individuals must occur between their 16th birthday and some distant time in the future (though they might die before it occurs). Thus, for this sampling design, all subjects contributing censored observations would be placed in a category of their own, a category on the underlying latent scale that extended from the last extimated threshold to infinity. Analysis then proceeds in the usual fashion as if there were no censored data.

In practice it is rare that subjects are interviewed on their birthdays. Continuing with the above example, they would be more likely to have been last interviewed some time following their 16th birthday, a time of varying duration depending upon the practicalities of fieldwork. With intervals of age of onset defined by chronological age, there will be some subjects who, though having no recorded onset by their 16th birthday, may have experienced onset in the period between that birthday and interview. For this approach such subjects would continue to be pooled with those subjects still without onset at the time of interview. Subjects in the latter category would thus be a mixture of censored and uncensored observations but all remain properly described as not having experienced onset by their 16th birthday. This follows the treatment of observations in the discrete time hazards models of Aitkin *et al.* (1989, p. 314), with censored observations being treated as censored at the start of the interval in which they were last observed. Again, analysis proceeds in the usual fashion.

CENSORED SURVIVAL DATA FROM TWINS WITH SLIGHT VARIATION IN AGE

Adapting the above solution to data from subjects of mixed age relies on simply extending the last category where censored observations are allowed. To illustrate this, first consider a situation where subjects differ slightly in age, say being a mix of 15 and 16 year olds. If we are willing to throw away some information, by taking the start of the last interval as being age 15 rather than 16, then we could proceed as before. What we have lost is the information that distinguished individuals who experienced onset between age 15 and age 16 from those who still had not by age 16—both are being described as having survived without onset to age 15. If most onsets commonly occur before age 15, this may reflect only a minimal loss of information.

CENSORED SURVIVAL DATA IN STUDIES WITH WIDE VARIATION IN AGE

The above approach loses any discrimination in ages of onset for onsets occurring at ages greater than that of the youngest individual. Clearly, extending this approach of reducing the age corresponding to the start of the last interval to the minimum age that any individual was last observed results in more and more loss of information as this minimum age declines. To solve this problem we group subjects by current age and fit the model as a multigroup problem, using the approch of Allison (1987) and Muthen *et al.* (1987) within each age group.

Within each group the minimum observed age is used as the start of the last interval as in Section 3, but this minimum varies from group to group. For onsets recorded (or being analyzed) within yearly intervals, forming groups of individuals defined by years of age would result in all the available information being used. Constraining all parameters, including thresholds, to be equal across all such groups then ensures that the same expected age-at-onset distribution is used for all subjects.

AN EXAMPLE: AGE-OF-ONSET OF PUBERTY IN BOYS

To illustrate this approach, we selected some preliminary data from the Virginia Twin Study of Adolescent Behavioral Development (VTSABD), in which an epidemiological sample of twins aged 8–16 years of age was assessed in a variety of areas (Hewitt *et al.*, 1994). This longitudinal multiple cohort study is following children initially aged be-

Table I. Age of Voice-Breaking in Male Twins from the VTSABD Study: Univariate Data

	MZ twin numbers			DZ twin numbers		
Age	At risk	On-set	Censored	At risk	On-set	Censored
8	242	0	22	230	0	14
9	212	0	30	192	0	38
10	190	0	22	163	6	29
11	159	5	31	131	5	26
12	121	17	33	108	14	18
13	89	29	15	76	21	18
14	51	29	9	44	23	11
15	18	10	4	17	11	4
16	1	1	7	1	1	5
17	0	0	0	0	0	0

tween 8 and 16. Table I shows the data on reported voice breaking from the Child and Adolescent Psychiatric Assessment (CAPA) maternal interview (Angold *et al.*, 1989) in the survival model format, with censored observations being treated as already described. Each boy is understood as having been "at risk" from birth up to their current age or the observed age at onset, whichever was the sooner. In fact the youngest recorded age of voice breaking was 10 [6 such boys among the dizygotics (DZs)]. Taking the age 12 interval for the monozygotic (MZ) twins as an example, at the start of the interval there were 121 boys at risk of onset during that interval, and from among these, 17 were recorded as experiencing it. The number at risk at the start of the age 13 interval is obtained by subtracting the number experiencing onset in the previous interval (17) and the number censored at the start of the interval (15) from the previous at-risk number, to give 89 (121-17-15).

The distribution of the ages of the twins in the study has resulted in many of the observations being censored. Using only data on twins aged 16 or older, the crosstabulated ages at onset by yearly interval, with censored observations being placed in the last interval, are as shown in the top of Table 2. Observations from only 14 MZ and 13 DZ pairs could be used. Below these data are shown those obtained from the 15-year-old boys, a further 15 MZ and 10 DZ pairs. As age declines, so an increasing proportion of the twin pairs fall in the botton right-hand cell, and such tables generally provide less and less useful information for the analyis. By age 10 all twin pairs were placed into a single cell of the table and thus provided no useful data for the analysis. However, using the tables from those aged from 11 upward allows data from 95 MZ and 80 DZ pairs to be included in the analysis.

Although we have performed the main computation using these 12 groups of twins (6 MZ and 6 DZ), fewer groups could be used using the approach outlined in Section 3. If carefully done, relatively little loss of useful information need occur. The details of the basic analysis using Mx are shown in the Appendix for just the two age groupings shown in Table III, the 16+ group and a pooling of those aged 14 and 15. Although this simplified approach makes use of only 44 MZ and 40 DZ pairs, as explained above they are likely to be the most informative pairs.

The most important point that differentiates the Mx setup of the Appendix from the standard analysis of ordinal data are the cross-group constraints. Specifically, the constraints on thresholds across all groups imply that thresholds 1 and 2 are the same for the twin pairs forming the 5×5 tables as for those forming the 3×3 tables. Thus the probability of a randomly sampled 14- or 15-year-old experiencing onset in interval 1 or 2 is the same as that of a randomly sampled child of 16 or more. Correspondingly, the probability of a 14-year-old child, by experiencing onset or by censoring, falling into the third interval of the 3×3 table, is equal to the probability of a 16-year-old child experiencing onset in the third and fourth intervals or by onset or censoring falling into the fifth interval of the 5×5 table.

Table IV presents the results of model fitting using the four groups in Table III. Table V gives those for the 12 groups in Table II. The fitted models were of the standard ACE form (e.g., Neale and Cardon, 1992, p. 153) and were estimated with and without genetic effects. The sparseness of the contingency tables means that the goodness-of-fit chi-square approximates rather poorly the nominal chi-square distribution and is thus not expecially informative about the overall fit of the model (Agresti, 1990). However, the LR chi-square obtained as the difference in the fit of nested models remains well behaved and gives values of 14.22 ($p < .001$) and 25.32 ($p < .001$) for the 1 df test of genetic effects in the 4-group and 12-group analyses, respectively. The parameter estimates also suggest that genetic effects are the most important

Table II. Age of Voice-Breaking in Male Twins from the VTSABD Study: Bivariate Data

	MZ Twin 2							DZ Twin 2						
	10	11	12	13	14	15	16+	10	11	12	13	14	15	16+
Twins aged 16 or more														
Twin 1														
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	1	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	2	0	0	0	0	0	0	1	1	0	0
14	0	0	0	0	2	1	0	0	0	0	1	2	1	1
15	0	0	0	0	0	3	2	0	0	0	0	1	1	2
16+	0	0	0	0	0	0	3	0	0	0	0	0	1	1
Twins aged 15														
10	0	0	0	0	0	0		0	0	0	0	0	0	
11	0	0	0	0	0	0		0	0	0	0	0	0	
12	0	0	1	0	0	0		0	0	0	0	0	0	
13	0	0	1	2	0	0		0	0	0	0	0	2	
14	0	0	0	0	7	1		0	0	2	0	1	1	
15	0	0	0	0	2	1		0	0	1	0	2	1	
Twins aged 14														
10	0	0	0	0	0			0	0	0	0	0		
11	0	0	0	0	0			0	0	0	0	0		
12	0	0	1	0	1			0	0	0	0	2		
13	0	0	0	5	0			0	0	1	5	0		
14	0	0	0	1	7			0	0	0	2	7		
Twins aged 13														
10	0	0	0	0				0	0	0	0			
11	0	0	0	0				0	0	0	0			
12	0	0	3	1				0	0	1	2			
13	0	0	1	11				0	0	0	9			
Twins aged 12														
10	0	0	0					1	0	0				
11	0	2	0					0	0	2				
12	0	0	17					0	2	9				
Twins aged 11														
10	0	0						0	0					
11	0	16						1	13					
These last 2 add no information														
Twins aged 10														
10	11							16						

source of variation in age-of-onset of male puberty. These results are in good agreement with previous results (Pickles *et al.*, 1994) obtained from a piecewise exponential proportional hazards model with genetically structured random effects that followed a variety of distributional forms.

The estimated probability of "surviving" to the kth age interval without experiencing onset is given by one minus the area of the normal curve from minus infinity to the $(k\text{-}1)$th threshold. This expression, evaluated at each age, gives the survivor function shown in Fig. 2.

COHORT, PERIOD, AND RECALL BIAS EFFECTS

An explicit assumption of the above approach is that the same model is fitted to twins of all ages. Depending upon the sample design, this specifically excludes some or all of cohort effects, period

Table III. Age of Voice-Breaking in Male Twins from the VTSABD Study: Grouped Bivariate Data

	MZ Twin 2					DZ Twin 2				
	12	13	14	15	16+	12	13	14	15	16+
Twins aged 16 or more										
Twin 1										
12	1	0	0	0	0	0	0	0	0	0
13	0	2	0	0	0	0	1	1	0	0
14	0	0	2	1	0	0	1	2	1	1
15	0	0	0	3	2	0	0	1	1	2
16+	0	0	0	0	3	0	0	0	1	1
Twins of age 14 or 15										
	12	13	14+			12	13	14+		
12	2	0	1			0	0	2		
13	1	7	0			1	5	2		
14+	0	1	18			3	2	12		

Table IV. Parameter Estimates and Goodness of Fit: Two-Age Group Model

	Environment only	Genes & environment
Standardized variances		
Genetic	0.00	0.93
Common environment	0.64	0.00
Specific environment	0.36	0.07
Thresholds		
1	−1.34	−1.34
2	−0.53	−0.53
3	0.17	0.17
4	0.89	0.89
χ^2	61.01	46.79
df	58	57

effects, and recall bias effects (and possible interactions involving such effects). In general, cohort and period effects can be a major problem, for which there is a substantial literature (e.g., Holford, 1992). Over the century evidence for cohort and period effects on age of puberty is strong, arising from the general trend of improvement in nutrition with, in some populations, occasional reversals due to starvation. However, in the example considered here, with closely grouped cohorts and a relatively stable population and environment, such gross effects would seem implausible. More worrying are the potential effects of recall bias. Omission or invention of the pubertal event would seem unlikely in this study because, in the instance of voice-breaking, both interviewer and mother could check the response against each twins' current status. A more likely problem was the misplacement in time of the pubertal event.

A phenomenon that is that thought to be common (Janson, 1990, Sudman and Bradburn, 1973), Bachman and O'Maley 1981, Bradburn *et al.*, 1987) is the occurrence of "telescoping" of more distant past events into the more recent past. Specific studies comparing medical records with women's retrospective reports on their own age at menarche have found evidence of heaping at multiples of 12 months, but otherwise the errors were generally symmetrically distributed around zero and thus without apparent telescoping (see Holt *et al.*, 1991). Nonetheless, voice-breaking in one's sons may be less memorable and salient than one's own age at menarche and, thus, may be more subject to asymmetric distortion. The mothers of older twins will be attempting to recall the pubertal event from a more distant point in the past than mothers of younger twins. The presence of telescoping in these data is suggested by noting that in Table II the earliest clear onsets of puberty (two MZ pairs at 11, one DZ pair at 10, and single DZ twins at 10 and 11) are all reported for children aged 12 or less at the time of interview.

In the simplified approach, with just two age groups, it is a simple matter to allow one set of thresholds for the mothers of boys aged 16 and another for the mothers of boys aged 14 to 15. Relaxing the constraint of shared thresholds results in just two extra parameters being estimated. However, extending this approach to the analysis with six age groups would result in the need to estimate a large number of threshold parameters (21 possible thresholds, although only 13 would have been empirically identified in this example). A more focused model of telescoping effect can be constructed as shown in Fig. 3 for a hypothetical three-threshold, three-age group example. It would seem reasonable that recall bias does not influence current status, so that for each age group the threshold that delineates those who have, and those who have not, experienced onset would be the "true" threshold. However, thresholds in the past are all subject to a systematic bias that displaces events to the right or, alternatively, displaces the effective thresholds to the left. The amount of displacement would be likely to increase with how far back in

Table V. Parameter Estimates and Goodness of Fit: Six-Age Group Model

	Environment only	Genes & environment	Genes, environment & telescoping						Genes & environment, current-status data
Standardized variances									
Genetic	0.00	0.85	0.91						0.89
Common environment	0.79	0.10	0.00						0.00
Specific environment	0.21	0.05	0.09						0.11
			Age 11	Age 12	Age 13	Age 14	Age 15	Age 16	
Thresholds									
1	−2.47	−2.41	−1.81	−2.35	−2.56	−3.33	−5.63	−5.63	−2.06
2	−1.79	−1.76		−1.31	−1.86	−2.07	−2.83	−5.14	−1.02
3	−0.98	−0.99			−0.55	−1.10	−1.31	−2.08	−0.82
4	−0.31	−0.34				−0.16	−0.71	−0.92	−0.08
5	0.45	0.45					0.48	−0.06	0.57
6	1.09	1.08						0.73	0.65
χ^2	156.81	131.49	99.28						23.19[a]
df	258	257	252						27

[a] Estimated on different data and thus chi-square not comparable with those from other models.

time the subject is being asked about but might not depend on their actual age. In Fig. 3 this is illustrated by displacement d_2 being larger in magnitude than d_1, but the same displacements being used with each age group. Thus in our actual example, a mother of a 16 year old would be expected to displace the 14-year threshold farther than the 15-year threshold. However, a mother of a 16 year old might displace the 15-year threshold the same amount as the mother of a 15 year old would displace the 14-year threshold.

The results of fitting a model that included telescoping effects to the data in Table II are shown in Table V. The addition of the five displacement parameters gave a very substantial reduction in the model χ^2 of 32.21 ($p < .001$), suggesting telescoping effects to be pronounced in these data. As shown in Table V, the displacement parameters result in different thresholds by age group. Those that fall on the diagonal correspond to the notionally true thresholds not subject to telescoping. Thresholds are then estimated as being displaced from these diagonal values by −0.55 units for 1-year recall (e.g., −2.35 − 1.81 or −1.86 − 1.31), −0.76 for 2 years (e.g., −2.56 − 1.81 or −2.07 − 1.31), −1.52 for 3 years, −3.82 for 4 years, and again, −3.82 for 5 years (the equality in the last two values arises because of an identifiability problem due to the sparseness of the data). A simplified model was also fitted in which the displacements grew logarithmically, such that $d_j = d[1+\log(j)]$. This simplified model fitted almost as well and gave, compared to the second model in Table V, a 1-df χ^2 for telescoping effects of 27.56 ($p < .001$).

Mothers report on both their twins, and thus the ages of onset of both twins are subject to this recall bias effect, MZ and DZ alike. Not surprisingly, therefore, accounting for telescoping substantially reduced the apparent effects of common environment, leaving almost all the variance as being due to genetic and specific environment effects.

Telescoping involves the shifting of events in one direction only, forward in time and thus closer to the present. An alternative recall bias that could give a similar effect is the shifting of dates toward a commonly held "normative age." For boys still to experience onset, no shifting of reported age of onset to a younger age is possible without the report conflicting with "current-status" evidence. Thus a systematic forward shift can occur either because the believed normative age was higher than the true normative age or because, though

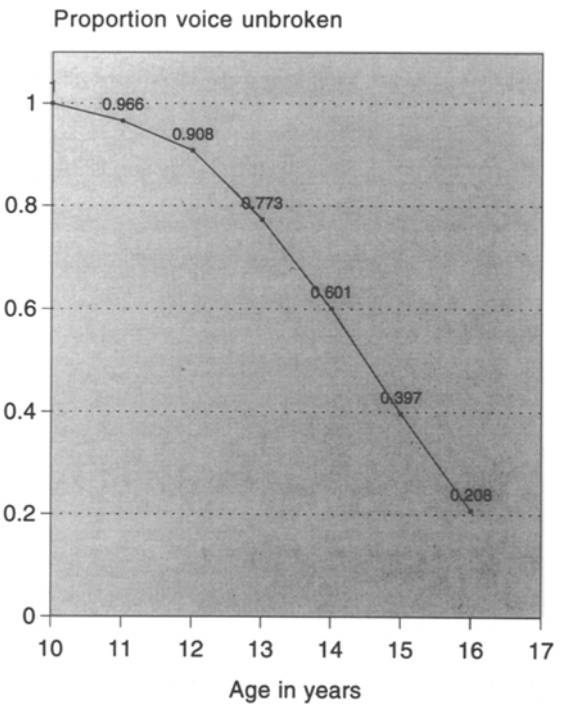

Fig. 2. Survivor function for onset of puberty.

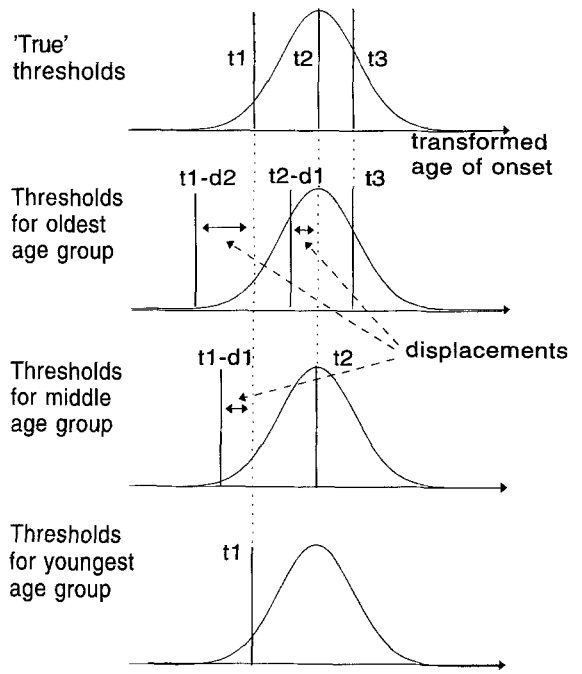

Fig. 3. Thresholds and their displacement by "telescoping" memory effects.

there was no bias in the believed normative age, the data were (as here) heavily censored. The issue is made still more complicated by the fact that each mother is reporting on both twins and the errors in the dating of the pubertal event for one twin may not be independent of the errors in the second. The problem is analogous to that in obtaining birth histories by retrospective methods (see Hobcraft & Murphy, 1987) for which interevent times may be better recalled than absolute times. Thus where both twins are postpubertal, the dating of onset of one twin may be subject to various forms of error, but that date is then used as a "marker," with the onset of the second being placed an accurately remembered amount of time before or after it.

Complications of this sort have persuaded some demographers that it is only the data on current status that provide a valid basis for inference (Diamond and McDonald, 1992). Fortunately, a genetic analysis based on current-status data alone is easily implemented. The $n \times n$ data table for each group is replaced by the 2×2 table formed by collapsing rows and columns 1 to $n-1$. The tables thus divide each group simply into those who have experienced onset at the start of the last interval (of that age group) and those who have not. In each age group only a single threshold is estimated and there are no constraints on the values of these thresholds from age group to age group. The age-of-onset distribution is thus estimated entirely from the cross-sectional information in the sample. The results from the "robust" approach are shown in the last column in Table V. These are very similar to those from the model involving telescoping effects.

Increased robustness is usually gained at the expense of efficiency. In this case, however, for the genetic effects of primary interest the cost does not seem too high, since the χ^2 for removing genetic effects obtained from the model based on current-status data alone was 7.76, only slightly lower than the χ^2 of 8.58 obtained from the more restrictive telescoping model.

DISCUSSION

This paper shows how two of the major stumbling blocks to the twin analysis of age-at-onset data can be overcome. First, the paper shows how

genetic models can be fitted to such data with software now in common use with twin researchers. Second, some of the major concerns about measurement error in retrospective recall, perhaps the most common source of age-of-onset data, have been addressed. It has been shown how inference is possible by extending the model to cover hypothesized forms of measurement error, using as an example an extended model that included telescoping effects. Alternatively, inference can be based solely on the part of the data thought to be most valid, namely, the current status data.

A further extension of the model is possible for circumstances where systematic recall bias effects vary with measured characteristics of the subjects, reporting source, or interviewer. For such data the magnitude of the displacement parameters can be allowed to vary with these measures, for example, by grouping or by means of a regression type function.

APPENDIX

Mx Setup for Two-Age Group Model in Table IV

```
MZ twins aged 16 and 16+, 5 categories
Data Ninput=2 Ngroup=5
Ctable 5 5
1 0 0 0 0
0 2 0 0 0
0 0 2 1 0
0 0 0 3 2
0 0 0 0 3
Matrices
A full 1 3 free                          ! For common model—paths from A
T full 2 4                               ! Common Thresholds
Bsymm 6 6                                ! MZ covariance of genetic and environmental variables
I iden 2 2                               ! to assist creating model
Thresholds T /
Covariance model \ stnd((I@A)*B*(I@A)') /
Specifications A
1 2 3
Labels Col A
At1 Ct1 Et1
Matrix A
.0 .5 .5                                 ! To start estimation at 50% each Specific & Shared Envt
Boundary 0.00001 1 1 2 3                 ! To keep the parameters positive
Specify T                                ! Constrain row (twin1) and column (twin2) threshold equal
4 5 6 7
4 5 6 7
Matrix B
1
0 1
0 0 1
1 0 0 1
0 1 0 0 1
0 0 0 0 0 1
Labels Row B
```

```
At1 Ct1 Et1 At2 Ct2 Et2
Labels Col B
At1 Ct1 Et1 At2 Ct2 Et2
Option rs
End
DZ twins, 5 categories
Data Ninput=2
Ctable 5 5
0 0 0 0 0
0 1 1 0 0
0 1 2 1 1
0 0 1 1 2
0 0 0 1 1
Matrices
T full 2 4 = T1                    ! Common thresholds
A full 1 3 = A1                    ! For common model—paths from A to P
B symm 6 6                         ! DZ covariance of genetic and environmental variables
I iden 2 2                         ! to assist creating model
Thresholds T /
covariance_model \stnd((I@A)*B*(I@A)') /
Matrix B
1
0 1
0 0 1
.5 0 0 1
0 1 0 0 1
0 0 0 0 0 1
Option rs
End
MZ twins aged 14/15, 3 categories (equivalent to pooling categories 3, 4, & 5)
Data Input=2
Ctable 3 3
2 0 1
1 7 0
0 1 18
Matrices
T full 2 4 =T1                     ! Common thresholds
A full 1 3 =A1                     ! For common model—paths from A to P
B symm 6 6 =B1                     ! MZ Covariance of genetic and environmental variables
I iden 2 2
Threshold T /
Covariance_model \stnd((I@A)*B*(I@A)') /
Option rs
End
DZ twins, 3 categories
Data Ninput=2
Ctable 3 3
0 0 2
1 5 2
```

```
3 2 12
Matrices
T full 2 4 = T1                    ! Common Thresholds
A full 1 3 = A1                    ! For common model—paths from A
B symm 6 6 = B2                    ! DZ covariance of genetic and environmental variables
I iden 2 2
Thresholds T /
Covariance_model \stnd((I@A)*B*(I@A)')/
Option rs
End

Calculate Standardized Estimates
Data calc
Matrices
X Full 1 3
Compute X.X@(X*X')~/
Specify X 1 2 3
Option rs
End
```

ACKNOWLEDGEMENTS

This work was supported by Grants MH45268 and MH48604. We thank Julie Taylor and Louis Sim for help in data management.

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Edited by N. G. Martin