Growth curve models and panel dropouts: Applications with criminological panel data

Several statistical models exist to study panel dropouts with respect to the underlying missing data mechanism. The paper discusses two models which extend the classical growth curve model: the selection model and the pattern mixture model. Specific variants of these models are applied with five-wave data from a criminological panel study. The selection model shows that the observed variable has an influence on the rate of panel dropouts within the same panel wave when the average delinquency rate has its peak. In this case the dropout process is not missing at random. With decreasing delinquency the results suggest that the dropout process is missing at random. In addition, the pattern mixture model is able to identify the class of respondents with the highest amount of dropouts which are also those ones which reach the highest delinquency rates in the entire time range of the study.

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Introduction

Several research attempts has been made to cope with missing data for different survey designs. The methodological literature has mostly discredited simple and easy to use methods that discard incomplete cases from the substantive analysis (listwise or pairwise deletion of missing data) or techniques that replace the missing values with a single set of values (e.g., mean imputation). More advanced techniques such as multiple imputation or full information maximum likelihood have been proposed as appropriate under certain conditions relating to the mechanisms that produce the missing data (for an overview see Enders, 2010).

Rubin (1987) distinguishes three different missing data mechanisms: missing completely at random (MCAR), missing at random (MAR) and not missing at random (NMAR). Following the notation of Little and Rubin (2002) the vector of observed data is Y_{obs}; the vector of missing data is Y_{mis}: $Y = (Y_{obs}, Y_{mis})$. A missing data matrix $M(=M_{ij})$ provides the information if, for a person i, the value of a variable j is missing (M_{ij}=1) or not (M_{ij}=0). ψ denotes the parameter vector influencing the probability of missing data. θ contains the parameters of substantive interest.

The missing data mechanism is MCAR when the probability of missing values on a variable does not depend either on the observed values Y_{obs} or the missing values Y_{mis}: $f(M|Y, \psi) = f(M|\psi)$. The assumption of MCAR is required with listwise deletion since observed values for cases with missing values on variables under study are discarded. Under MCAR complete cases are a simple random sample of all cases. The missing data mechanism is MAR when the probability of missingness depends on the observed values, but is unrelated to the missing values: $f(M|Y, \psi) = f(M|Y_{obs}, \psi)$. Additionally it is required that θ and ψ are distinct parameters. MAR is a weaker assumption than MCAR. If the missing data mechanism is MAR likelihood-based conclusions about the parameters of substantive interest (θ) are possible without information about the parameters ψ that govern the missing data process (Little & Rubin, 2002, p. 119). Full information maximum likelihood and multiple imputation produce unbiased parameters under MAR. In contrast to listwise deletion (LD) available data are employed. Finally, the process of missingness is not missing at random (NMAR) when the process of missingness also depends on the missing values themselves: $f(M/Y, \psi) = f(M/Y_{mis}, Y_{obs}, \psi)$. The missing data mechanism cannot be ignored because the missing data contain information about the substantive parameters theta.

In case of NMAR it is necessary to explore and model the missing data mechanism together with the substantive application. Selection models and more advanced variants of pattern mixture models for panel data were recently discussed within the context of Psychology and Methodology (Enders, 2010; Enders, 2011; Muthén, Asparouhov, Hunter, & Leuchter, 2011). These models are extensions of the classical growth curve model which is able to separate intra- and interindividual development of observed measurements (Meredith & Tisak, 1990).

Based on these discussions this paper focuses on applications of a selection and a pattern mixture model for criminological panel data to explore whether permanent and temporary panel attritions are due to MAR or NMAR mechanisms. The following section starts with a brief description of the latent growth curve model followed by the extensions to selection and pattern mixture models. Then the criminological panel data used for the applications are described, followed by the results of the models estimated with the program M*plus* (Muthén, 1998-2010). Finally, a discussion and concluding remarks will be provided.

Models

Growth curve models

The possibility that the individual trajectories of a dependent variable can vary is one of the main advantages of the growth curve model. The formal representation of a growth curve model can be seen either as a multilevel, random-effects model or as a latent variable model, where the random effects are latent variables (Meredith & Tisak, 1990, p. 108; Willett & Sayer, 1994, p. 369):

$$y_i = \Lambda \eta \varepsilon_i \qquad (1)$$

y_i is a $t \times 1$ vector of repeated measurements for observation i where t is the number of panel waves. η is a $q \times 1$ vector of latent growth factors where q is the number of these factors. ε is a $t \times 1$ vector of time-specific measurement errors, and Λ is the $t \times q$ matrix of factor loadings with fixed coefficients representing the functional form of the individual trajectories. Variations of individual trajectories are captured by q-numbers of latent variables η whereas usually η_1 is the *intercept*, η_2 is the *linear slope* and in case of nonlinear development η_3 represents the *quadratic slope* (cf. Figure 1).[1] If applicable, additional latent variables can be specified. It is assumed that the latent growth factors and measurement errors are independent and multivariate normally distributed:

$$\begin{bmatrix} \eta \\ \varepsilon_i \end{bmatrix} \sim \left(\begin{bmatrix} \alpha \\ 0 \end{bmatrix}, \begin{bmatrix} \Psi & 0 \\ 0 & \Theta \end{bmatrix} \right) \qquad (2)$$

where α is a $q \times 1$ vector of growth factor means and Ψ is the respective $q \times q$ covariance matrix. Θ is a $p \times p$ covariance matrix of time-specific measurement errors which are usually constrained to be a diagonal matrix. For estimation a probability density function is used:

$$f(y_i) = \phi\, [y_i; \mu(\theta), \Sigma(\theta)] \qquad (3)$$

where ϕ is the probability density function for y_i and θ is the vector of all parameters to be estimated. $\mu(\theta)$ is a p × 1 model-implied mean vector given by

$$\mu(\theta) = \Lambda \alpha \qquad (4)$$

and $\Sigma(\theta)$ is a p × p model-implied covariance matrix given by

$$\Sigma(\theta) = \Lambda \Psi \Lambda' + \Theta \qquad (5)$$

Parameters in θ can be estimated by ML, maximising the likelihood that the measurements y_i are drawn from a multivariate normal distribution. The means of the latent growth factors α show the average development of the measurement y_i across p panel waves within a homogenous population.

Selection and pattern mixture models

For regression analyses the selection model of Heckman (1976, 1979) is often applied as a bias correction method with NMAR data on the particular variable under study. This selection model has

[1] I prefer to discuss the growth curve model with three latent variables η because the observed variable y_t in the applications in the next section shows a nonlinear development over time.

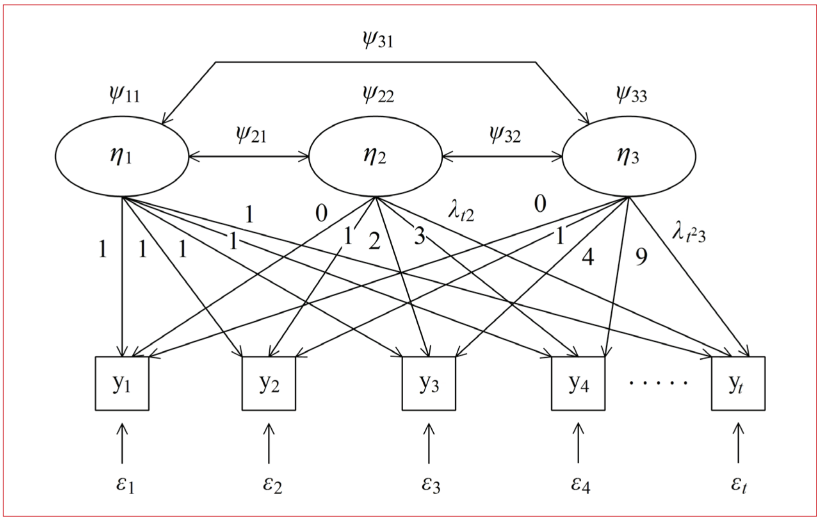

Figure 1 Quadratic growth curve model for t panel waves

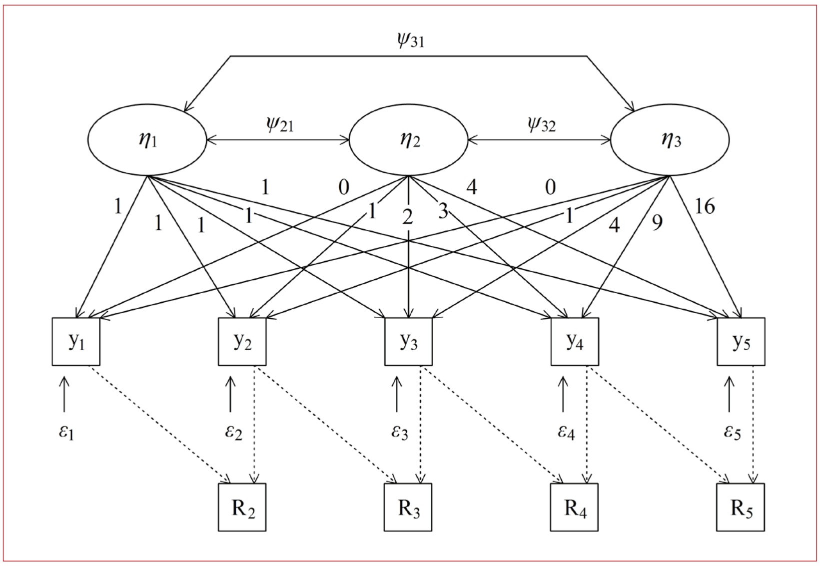

Figure 2 Quadratic growth curve model with indicator variables according to Diggle and Kenward (1994)

two parts: one part consists of the substantive regression equation, the other part predicts the response probabilities with an additional equation. Selection models for longitudinal data also combine a substantive model with additional equations to predict the missingness of the data. In this paper missingness refers to permanent or temporary dropout from a panel study. The substantive part of the model can be analysed with growth curves whereas the methodological part of the model contains logistic regressions predict the missing data indicators. Numerous model formulations are discussed throughout the statistical literature but two longitudinal selection models have been proposed and applied recently (Enders, 2010, p. 304f.; Enders, 2011, p. 7):

1. The selection model of Wu and Carroll (1988) uses growth curve variables to predict the probability of missing data. This model contains missing data indicators R_t which denote whether the observed variable y at a particular panel wave t is observed or not. The indicator variables are regressed on the growth curve part of the model via logistic or probit regression equations. If panel data with five waves are used the model contains five observed variables ($y_1,\ldots\ldots,y_5$) and five indicator variables ($R_1,\ldots\ldots,R_5$). Here, the probability to remain in the panel is dependent on the random coefficients of the developmental process. For example, the higher the linear slope the more probable are the dropouts of respondents. Linking the response probabilities to the growth curve variables might be useful when the dropout process depends on the overall trajectory (for applications see Enders, 2011 and Reinecke, 2012). The model assumes that observed variables y_t are uncorrelated with indicator variables R_t. Detection of a specific MAR or NMAR dropout mechanism related to particular panel waves seems to be difficult. In addition, variances of the quadratic terms of the models are often too small to explain the probability of missingness. Therefore, the model of Wu and Carroll (1988) will not be considered for the applications.

2. The selection model of Diggle and Kenward (1994) contains the same variables but the indicator variables R_t are regressed directly on the observed variables y_t as well as on the lagged variable y_{t-1} (Figure 2). The significance of the logistic regression coefficients (dashed lines in the figure) allows conclusion about the missing data mechanism: If there are no relationships between y_t, y_{t-1} and R_t, the dropouts are unrelated to the observed variables which would follow a MCAR mechanism. If the lagged variable y_{t-1} has an potential impact on R_t, the mechanism is MAR. That means, dropout at time t is related to the observed values from the previous panel wave. If significant within-wave relationships between R_t and y_t are detected, a NMAR mechanism is plausible. That means dropout at time t is related to the observed values from the same panel wave. The model assumes a multivariate normal distribution for the continuous variables y_t.

An alternative framework to model NMAR dropout mechanism is the pattern mixture model. This approach defines subgroups of cases with the same missing data pattern and estimates the substantive model within each group or pattern. The pattern-specific estimates can be averaged across the groups to get a single set of estimates that account for the NMAR mechanism (cf. Enders, 2010, p. 299). But, some of the parameters are not estimable and identifying restrictions have to be specified. Combining the indicator variables R_t with a quadratic

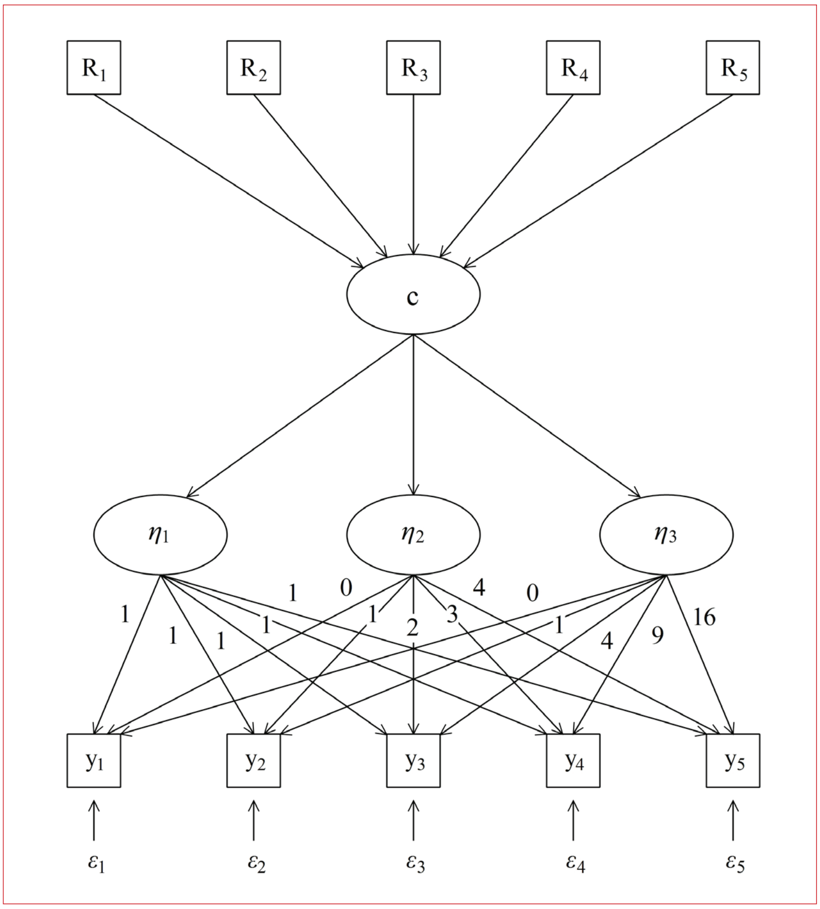

Figure 3 Latent dropout pattern mixture model (Roy, 2003)

growth curve model leads to some non-identified parameters (e. g. the means of the linear and quadratic slope for respondents dropping after t_1 and the mean of the quadratic slope for respondents dropping out after t_2, see Muthén et al., 2011, p 20). Equality restrictions to other dropout patterns can be applied and solve the identification problem. Despite of the fact that wrong restrictions can lead to substantial bias the pattern mixture model assumes that every respondent with the same dropout time has a common distribution, i. e. the sample under study is homogenous in that respect. To overcome this assumption of homogeneity Roy (2003) proposed a *latent dropout pattern mixture model* where a class variable *c* is influenced by the dropout indicators R_t (Figure 3). Variables R_t and latent class variable *c* are connected via a multinomial logistic regression model:

$$P(c_i = k \mid R_{1i} \ldots R_{Ti}) = \frac{e^{\gamma_{0k} + \sum_{t=1}^{T} \gamma_{tk} R_{ti}}}{\sum_{s=1}^{K} e^{\gamma_{0s} + \sum_{t=1}^{T} \gamma_{tk} R_{ti}}} \qquad (6)$$

Equation 6 estimates the probability that a panel dropout for a particular class is higher or lower than for the reference class. Latent class variable *c* itself influences the latent growth curve variables and models the unobserved heterogeneity of the development under study. Instead of considering individual variation of single means of the vector η the so-called growth mixture model (GMM) allows different classes of individuals to vary around different means (Muthén & Shedden, 1999):

$$y_{ik} = \Lambda_k \eta_{jk} + \varepsilon_{ik} \qquad (7)$$

Parameters of the model are estimated for $k = 1, \ldots, K$ latent classes. The number of categories of class variable *c* represent the degree of unobserved heterogeneity in the data. The probability density function for the GMM is a finite mixture of normal distributions:

$$f(y_i) = \sum_{k=1}^{K} \pi_k \phi_k [y_i; \mu_k(\theta_k) \Sigma(\theta_k)] \qquad (8)$$

π_k is the unconditional probability that a measurement belongs to latent class k, ϕ_k is the multivariate probability density function for latent class k. $\mu_k(\theta_k)$ represents the model-implied mean vector given by

$$\mu_k(\theta_k) = \Lambda_k \alpha_k \qquad (9)$$

and $\Sigma_k(\theta_k)$ is the model-implied covariance matrix given by

$$\Sigma_k(\theta_k) = \Lambda_k \Psi_k \Lambda_k^t + \Theta_k. \qquad (10)$$

The mixture model of Roy (2003) makes explicit use of the GMM and proposes that the dropout mechanism is related to the mixture of the growth curves.

The model is estimated by maximising the log likelihood function within the admissible range of parameter values given classes and data. The program M*plus* uses the principle of maximum likelihood estimation and employs the EM algorithm for maximisation (Dempster, Laird, & Rubin, 1977; Muthén & Shedden, 1999).[2] For a given solution, each individual's probability of membership in each class is estimated. Individuals can be assigned to the classes by calculating the posterior probability that an individual *i* belongs to a given class *k*. Each

[2] The integration method of M*plus* tests several sets of starting values evaluating the maximum initial stage log likelihood value. The seed number corresponding to that value is used for the final estimation of the model. For re-estimation of the model parameters the optimal seed value of the previous run can be included in the input file (for details see Muthén, 1998-2004).

individual's posterior probability estimate for each class is computed as a function of the parameter estimates and the values of the observed data (Muthén, 1998-2004).

It is always an empirical question how many classes are sufficient to describe the unobserved heterogeneity of the data. By classifying each individual into his most likely class, a table with rows corresponding to individuals classified into a given class can be constructed. The columns of that table show the average conditional probabilities to be in the particular class. Quality of the classification is summarised by the entropy measure E_k (Muthén, 1998-2004), which ranges from zero to one, where values close to one indicate a good classification of the data.

In mixture models a k class model is not nested within a $k + 1$ group model. Therefore, conventional mixture tests like the Akaike Information Criterion (AIC; Akaike, 1987), the Bayesian Information Criterion (BIC; Schwarz, 1978) or the sample-size adjusted Bayesian Information Criterion (SABIC; Sclove, 1987) have to be used for model comparisons.[3] If the k-class model contains a redundant class, the $k - 1$-class model with the smaller AIC, BIC or SABIC value should be chosen. An expansion of the model by adding a class is desirable only if the resulting improvement in the log likelihood exceeds the penalty for more parameters. But accepting or rejecting a model on the basis of the information criteria is more or less descriptive and does not imply any statistical test.

Lo, Mendell, and Rubin (2001) proposed a likelihood ratio-based method for testing $k - 1$ classes against k classes in mixture models. The Lo-Mendell-Rubin likelihood ratio test (LMR- LRT) considers the usual likelihood ratio for testing the $k - 1$ model against a k model but with the correct distribution. The p-value from the test represents the probability that H0 is true, i.e., that the model is sufficient with one less class. Therefore, a low p-value indicates that the $k - 1$ class model has to be rejected and the k-class model can be accepted for substantive interpretations. Information criteria and the LMR-LRT will be used for the selection of the appropriate number of classes on the Roy model.

Data

The selection and pattern mixture model of Diggle and Kenward (1994) and Roy (2003) will be applied with data from the Study 'Crime in the modern City' (CrimoC, see Boers, Reinecke, Mariotti, & Seddig, 2010). This ongoing prospective panel study started in 2002 in Duisburg, an industrial city of 500,000 inhabitants in western Germany, with nine annual data waves having been collected. The annual survey started in 2002 with 3411 pupils from the 7th grade of all school types. Their mean age was 13. 70% of the schools (40 out of 57) agreed to participate. From these, 87% of the 7th-graders participated in the first year, which represented 61% of all 7th-graders in Duisburg. In subsequent years, the rates of participation ranged from 84% to 92%.

The CrimoC study contains panel datasets covering different numbers of panel waves. The following analyses stem from a five-wave panel dataset covering the period from late childhood (conducted in the year 2002) to late adolescence (conducted in the year 2006). A panel dataset with the minimum information from at least two out of five panel waves contains 3909 persons. This dataset has 23 different dropout patterns in total. Table 1 summarises nine of the most frequent dropout patterns. Patterns 1 to 5 contain one-wave dropouts and the patterns 6 to 9 two- and three-wave dropouts. Respondents with cross-sectional data from one time point only are not considered. Comparisons with respondents who participated five years in a row (n=1552) show some differences in the distribution of gender and school type. The incomplete panel dataset (n=3909) contains more females, somewhat fewer respondents from lower junior high schools and more from grammar schools.

Sixteen different types of delinquent behaviour were measured by self-reports due to the period of the last 12 months. These types include violence, aggravated assault with or without a weapon, shoplifting, car and bicycle theft, vandalism, graffiti, scratching, drug consumption and drug dealing.[4] Prevalence of the 16 different offenses are summed up to an index for each panel wave. The index has a range between zero and 16. Higher index values indicate more versatile criminal activity. On average, the mean offense rate increases up to the second panel wave (average age of 15) and decreases thereafter. The curvilinear development (also described as age-crime curve) is typical for adolescents aged between 14 and 18 years and is labelled as an *adolescent-limited* type of delinquent behaviour (e.g. Moffitt, 1993). The index of five panel waves (y_t) will be used for the selection and pattern mixture models in the following section. Substantive analysis with the complete data pattern support the curvilinear development of delinquency and the use of quadratic

[3] The SABIC replaces N in the BIC formula with (N + 2)/24 and is included in the M*plus* output.
[4] Internet crime was not included because measurements were not conducted in the first two panel waves.

Table 1 Sample of missing data patterns

Pattern	2002	2003	2004	2005	2006	n
1	--	t_2	t_v	t_4	t_5	403
2	t_1	--	t_3	t_4	t_5	134
3	t_1	t_2	--	t_4	t_5	109
4	t_1	t_2	t_3	--	t_5	96
5	t_1	t_2	t_3	t_4	--	224
6	t_1	t_2	--	--	--	289
7	t_1	t_2	t_3	--	--	150
8	--	--	t_3	t_4	t_5	275
9	--	--	--	t_4	t_5	114

Table 2 Distributions of the indicator variable R for five panel waves (2002-2006)

Panel wave	Variable	n	%
t_1	R_1 (0)	3308	84.6
	R_1 (1)	601	15.4
t_2	R_2 (0)	3265	83.5
	R_2 (1)	644	16.5
t_3	R_3 (0)	3293	77.2
	R_3 (1)	289	7.4
	R_3 (2)	327	8.4
t_4	R_4 (0)	3510	89.8
	R_4 (1)	226	5.8
	R_4 (2)	173	4.4
t_5	R_5 (0)	3209	82.1
	R_5 (1)	467	11.9
	R_5 (2)	233	6.0

(0): Person is not missing, (1): Person has monotone missing pattern.
(2): Person has non-monotone missing pattern

growth curve models (see Mariotti & Reinecke, 2010).

Indicator variables R_t have three categories, one for respondents with no missing data, one for respondents with a monotone missing pattern and one for respondents with a non-monotone missing pattern. Only monotone patterns can occur for the first and second panel wave. Therefore, indicator variables R_1 and R_2 have two categories whereas R_3, R_4 and R_5 have three categories. The distributions are shown in Table 2. Regarding the last three panel waves 5.8% up to 11.9% of the respondents have a monotone dropout pattern. Between 4.4% and 8.4% show a non-montone dropout pattern for the same time period.

Results

Results of the Diggle and Kenward model (Figure 2) as well as of the Roy model (Figure 3) are presented and discussed as follows. Six variants of the Diggle and Kenward selection model are estimated with the program M*plus* (see Table 3). The models DK4, DK5 and DK6 consider the time-invariant variable gender which are related to the growth curve variables as well as to the indicator variables. Models DK2 and DK5 have a smaller number of parameters than DK1 and DK4 because the relations between observed variables y_t and R_t are restricted to be equal across time for $t = 3, 4, 5$. The relation between y_2 and R_2 is estimated separately. In the same way, the lagged relations between y_{t-1} and R_t are restricted to be equal for $t = 3, 4, 5$ and the lagged relation between y_1 and R_2 is estimated separately. The models postulate that time-related differences for the dropout mechanism occur only between t_1 and t_2 and not between t_2 and further panel waves. In model DK5 the relations between gender and indicator variable R_t are also restricted to be equal over time for $t = 3, 4, 5$.

Models DK3 and DK6 enlarge the time-invariant restrictions to all panel waves. There are no separate estimators for the path between y_2 and R_2 as well as for the path between y_1 and R_2. In model DK6 the relations between gender and indicator variable R_t are also restricted to be equal over all measurements.

Comparisons of the information criteria AIC show nearly equal values between DK1 and DK2 as well as between DK4 and DK5. The BIC values support the specification of models DK2 and DK6 whereas the SABIC values support the models DK2 and DK5. All in all, the models DK3 and DK6 seem to be too restrictive according to their AIC and SABIC values. Therefore, models DK2 and DK5 are accepted for a more detailed description and discussion.

The means of the growth curve variables confirm the curvilinear development of delinquency in model DK2 and model DK5 (see Tables 4 and 5): Intercepts and linear slopes have positive parameter estimates while the estimates of the quadratic slopes are negative. The development confirms the usual trend of the age-crime curve detected in other longitudinal studies (e. g. Wikström, Oberwittler, Treiber, & Hardie, 2012).

The within-time influences of the observed variable y_2 on to the indicator variable R_2 are positive and significant in both models indicating that dropouts of the second panel wave are related to the amount of delinquent behaviour in the same wave. This result provides evidence for an NMAR mechanism. The odds ratio for the significant path in model DK2 is 1.147 reflecting a slightly higher chance of dropouts for people with higher delinquent mean rates within the current panel wave (see Table 4). Nearly the same result is obtained in model DK5 (odds ratio=1.136, see Table 5). In contrast, the lagged

Table 3 Results of the Diggle and Kenward models

Model	Parameter	AIC	BIC	SABIC
Models without gender				
DK1	29	74108	74290	74198
DK2	25	74107	74264	74185
DK3	23	74126	74270	74197
Models with gender				
Model	**Parameter**	**AIC**	**BIC**	**SABIC**
DK4	36	72755	72980	72865
DK5	30	72752	72939	72844
DK6	27	72766	72935	72849

Table 4 Estimated parameters of model DK2

Variable	Intercept	Standard error	*z*-value	
Intercept	0.874	0.034	25.390	
Linear slope	0.354	0.034	10.336	
Quadratic slope	-0.101	0.008	-12.953	
Relation	**Regression**	**Standard error**	***z*-value**	**Odds ratio**
$y_1 \rightarrow R_2$	-0.018	0.031	-0.593	0.982
$y_2 \rightarrow R_2$	0.137	0.022	6.308	1.147
$y_{2,3,4} \rightarrow R_{3,4,5}$	0.079	0.013	6.144	1.083
$y_{3,4,5} \rightarrow R_{3,4,5}$	-0.003	0.018	-0.171	0.997

Table 5 Estimated parameters of model DK5

Variable	Intercept	Standard error	*z*-value	
Intercept	1.102	0.054	20.277	
Linear Slope	0.432	0.054	7.946	
Quadratic Slope	-0.115	0.013	-9.113	
Relation	**Regression**	**Standard error**	***z*-value**	**Odds ratio**
$y_1 \rightarrow R_2$	-0.023	0.031	-0.754	0.977
$y_2 \rightarrow R_2$	0.128	0.022	5.910	1.136
Gender $\rightarrow R_2$	-0.341	0.089	-3.874	0.711
$y_{2,3,4} \rightarrow R_{3,4,5}$	0.066	0.014	4.851	1.068
$y_{3,4,5} \rightarrow R_{3,4,5}$	-0.007	0.018	-0.373	0.933
Gender $\rightarrow R_{3,4,5}$	-0.375	0.064	-5.810	0.688

relationships between y_1 and R_2 are small and not significant in both models. For the subsequent waves the reported relationships have opposite results: The lagged relationships are now positive and significant and the within-time regressions are small and not significant. This result provides evidence for an MAR mechanism. Odds ratios for the significant paths are 1.08 and 1.07 reflecting a slightly higher chance of dropouts for people with higher delinquent mean rates in the particular previous panel wave. It seems to be obvious that with overall increasing delinquency rates in early adolescence the chance of temporary dropouts is higher for people with larger delinquency rates. With overall decreasing delinquency rates the dropout mechanism is changing from NMAR to MAR.

For model DK5 the negative influence of gender toward the indicator variable y_2 (odds ratio=0.71) and the other indicator variables (odds ratio=0.69) shows that female respondents have a lower chance of a temporary dropout than male respondents. Earlier analyses with similar panel data measuring self-reported delinquent behaviour have also shown that female respondents have a higher probability to remain in the study (Reinecke & Weins, in press).

The Roy model (Figure 3) considers unobserved heterogeneity in the sample due to the development of delinquent behaviour. Variation of the class variable c (number of classes) reflects the size of the unobserved heterogeneity. Each class represents a subgroup with different trajectories which can be related to dropout time. The following analysis varies the number of classes between one and six. In line with Equation 6 class specific logistic regressions between the indicator variables R_t and class variable c are estimated. For mixture models with two or more classes all or part of the logistic regression coefficients can be set equal within the classes. This would test the assumption that the dropout process within the classes is not dependent on the particular panel wave.

Table 6 gives an overview about the estimated models. Looking at the LMR-LRT, models with more than four classes produce redundant information in the additional classes (p-value>0.05). That applies for models without restrictions as well as for models with the time- related equality restrictions (Models with labels *eq* and *peq*). All in all, the restricted models have better model fits than the unrestricted ones. Models with three or four latent classes reflect the best mixture of the developmental trajectories. Previous mixture analyses have shown that those four different classes reflect a substantial decomposition of the developmental process in delinquent behaviour (cf. Mariotti & Reinecke, 2010; Reinecke, in press).

Additionally, for these models time-related equality restrictions of the logistic regression coefficients are separated between the first two and the last three panel waves (Models with the label *peq*). Recall, that R_1 and R_2 have only two categories and can only consider monotone dropouts (see Table 2). So, these models consider differences in the dropout process across the time range of the study. Therefore, the partly restricted mixture model with four classes showing a significant LMR-LRT (p-value=0.04) will be discussed in detail.

The trajectories of the four classes can be described

Table 6 Results of the mixture models

Classes	Parameter	E_k	AIC	BIC	SABIC	LMR-LRT	*p*-value
1	22	–	77428	77566	77496	–	–
2	31	0.942	75265	75460	75361	2152	0.00
2(eq)	27	0.941	75262	75432	75345	2125	0.00
3	40	0.944	73632	73883	73756	1629	0.00
3(peq)	34	0.945	73360	73844	73736	1612	0.00
3(eq)	32	0.950	73686	73887	73785	1548	0.06
4	46	0.939	72438	72727	72580	1251	0.05
4(peq)*	37	0.939	72431	72663	72545	1243	0.04
4(eq)	34	0.941	72445	72659	72551	1231	0.05
5	55	0.930	71653	71998	71823	792	0.32
5(eq)	39	0.937	71669	71913	71789	768	0.57
6	64	0.936	71068	71469	71266	595	0.26
6(eq)	44	0.933	71073	71349	71209	591	0.19

*(eq) gives the model results under the restriction that the logistic regression coefficients of all panel waves are set to be equal within the classes.(peq) gives the model results under the restriction that the logistic regression coefficients of the first two panel waves and the last three panel waves are set to be equal separately within the classes. *denotes the model discussed in detail.*

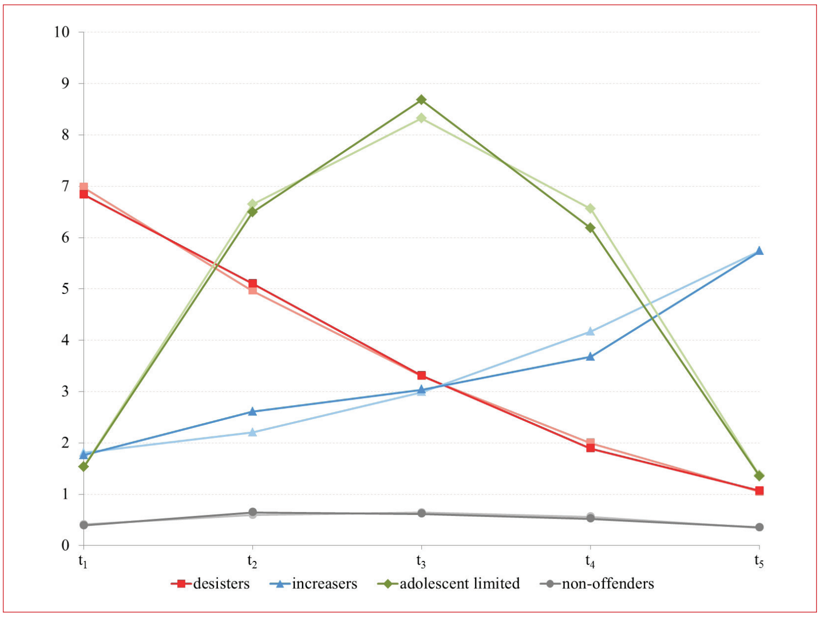

Figure 4 Observed and estimated trajectories of the Roy model with four classes circle = observed means, triangle = estimated means, description of the classes (from bottom to top): non-offenders, increasers, desisters, adolescent limited

as follows (cf. Figure 4): the class of *non-offenders* with almost no delinquency (n=3373), the class of *increasers* with a slow increase of delinquency (n=182), the class of *desisters* with high delinquency at wave one and a continuous decrease thereafter (n=207) and finally a class of people with a curvilinear trajectory reflecting an *adolescent limited* type of delinquent behaviour (n=147). There are only slight differences between observed and estimated means for all four trajectories.

Estimated logistic regression coefficients between indicator variables R_t and class variable c show the influence of the panel dropouts on to the class membership (Table 7). Reference category is class 4 (*non-offenders*). Recall that regression coefficients are set to be equal within classes for the indicator variables R_1 and R_2 and R_3 to R_5 respectively. Most relations are not significant due to the low number of cases. For class 1 (*desisters*) and class 2 (*increasers*) dropouts are not more likely compared with class 4 (*non-offenders*). But for class 3 the chance to drop off the study is much higher than for class 4 (odds ratio=2.243). This result holds for the first two panel waves. There is no similar effect regarding the last three panel waves. Again, the hypothesis that people with larger delinquency rates have a higher chance to drop off the study is supported. For subsequent panel waves the indicator variables have no significant effect on class 3 compared to class 4. With a decrease of delinquency after the third panel wave the chance to drop temporarily off the study is less likely.

Cross-tabulating the distribution of indicator variable R_2 with the distribution of the class variable c indicates that nearly one third of the people with an adolescent limited type of delinquent behaviour dropped temporarily off the study (54 out of 147) whereas the number of dropouts is much lower in the other classes (Table 8). Although relations of the other indicator variables are much smaller the tendency of a relationship between a temporary dropout and the delinquency rate is confirmed. In contrast to the Diggle and Kenward model the Roy model has the advantage that this relationship can be identified for a substantively important group of people, i.e., respondents with high levels of delinquency.

Conclusions

Procedures and techniques to handle missing data in cross-sectional as well as longitudinal designs are well-known and discussed under methodological considerations. Quite often the MAR assumption is reasonable, but in case the missing mechanism is related to the dependent observed variable itself MAR-based techniques would produce biased results. To consider missing data mechanisms in panel designs a substantive model (e.g., latent growth curve model) can be combined with an additional model that describes the dropout process across the panel waves. One possibility is the selection model of Diggle and Kenward (1994) which augments the growth curves with logistic regressions to estimate the probability of missing data at each wave depending on the substantive

Table 7 Logistic regressions of indicator variables R_t

Relation	Coefficient	Standard error	z-value	Odds ratio
R_1, R_2 → Class 1	0.064	0.157	0.407	1.066
R_3, R_4, R_5 → Class 1	0.136	0.090	1.511	1.146
R_1, R_2 → Class 2	0.176	0.289	0.608	1.192
R_3, R_4, R_5 → Class 2	0.008	0.107	0.076	1.008
R_1, R_2 → Class 3	0.808	0.161	5.023	2.243
R_3, R_4, R_5 → Class 3	-0.126	0.104	-1.221	0.881

Class 4 is the reference class (non-offenders).

Table 8 Relation between indicator variable R_2 and classes

R2	Classes				∑
	1	2	3	4	
0	159	159	93	2.854	3.265
	76.81%	87.36%	63.27%	84.61%	83.53
1	48	23	54	519	644
	23.19%	12.64%	36.73%	15.39%	16.47
∑	207	182	147	3.373	3.909
	100.00%	100.00%	100.00%	100.00%	100.00

variable. MAR as well as NMAR mechanisms can be detected. Another possibility is the pattern mixture model of Roy (2003) that makes use of the growth mixture approach (Muthén & Shedden, 1999). The dropout indicators is related to the latent class variable which reflects the degree of unobserved heterogeneity in the data.

Both models have been applied to data from a German panel study which explores the development of adolescents' delinquent behaviour (Boers et al., 2010). Five panel waves are used for the current analyses with respondents participating at least in two of the five waves. The development of delinquent behaviour is curvilinear which requires a latent growth curve model with an intercept, a linear and a quadratic slope. Results of the selection model of Diggle and Kenward (1994) indicate an NMAR mechanism for the first two panel waves while an MAR mechanism is detected for the last three panel waves. This result is also stable when the growth curve model is conditioned on gender. The NMAR mechanism occurs when on average the delinquency rate is increasing while the dropout seems to be MAR when on average the delinquency rate is decreasing. Results of the pattern mixture model of Roy (2003) complement the findings of the selection model. Dropout indicators of the first two waves have a significant influence on the class of respondents which follow an adolescent limited type of delinquent behaviour and have on average the highest delinquency rates across the time range of the study.

The application of the selection and pattern mixture model shows, in principle, the possibility to explore different dropout processes in panel studies due to MAR and NMAR mechanisms. Integration of a submodel that describes the propensity for missing data allows to identify the impact of the missing data mechanism on to the longitudinal results. The applied selection and pattern mixture models are capable to produce accurate parameter estimates when their requisite assumptions hold. But when the assumptions are violated they are also prone to substantial bias. Therefore, the current findings should be interpreted with caution. The logistic regression coefficients are small due to the low number of temporary dropouts. And only one effect is significant in the pattern mixture model for the smallest class of respondents. With further available panel waves the obtained results have to replicated. Other previous analyses in the same substantive context have also detected a significant relationship between the level of delinquency and the possibility to drop off at least temporarily from the longitudinal setting (Reinecke & Weins, in press).

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