

Developmental Pathways of Externalizing Behavior from Preschool Age to Adolescence: An Application of General Growth Mixture Modeling

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Abstract This study applies a developmental and life-course perspective on the data of the Erlangen-Nuremberg Development and Prevention Study (ENDPS; Lösel, Stemmler, Jaurisch, and Beelmann, *Monatsschrift für Kriminologie und Strafrechtsreform* 92:289–308, 2009) to find interindividual differences in intraindividual change of externalizing problem behavior. Based on a sample of $N = 541$ boys and girls, general growth mixture modeling (GGMM; Nagin, *Psychological Methods* 4:139–177, 1999; McArdle, *The handbook of research methods in developmental psychology*. New York: Blackwell Publishers, 2005) was applied. In a prospective longitudinal design measurements with multiple informants were analyzed from preschool to adolescence. The results of the GGMM showed five groups representing different developmental trajectories: (1) “*high-chronics*” (2.4 %; $n = 13$), who had the highest scores of externalizing behavior at all times; (2) “*low-chronics*” (58.8 %; $n = 317$) who were low on externalizing behavior throughout the years; (3) “*high-reducers*” (7.9 %; $n = 43$) who started out high, but reduced their externalizing behavior monotonically over time; (4) “*late-starters-medium*” who increased externalizing problems at later age (8.7 %; $n = 47$); and (5) “*medium-reducers*” whose problems decreased from an originally medium level (22.4 %; $n = 121$). The results are in accordance with international studies on developmental trajectories of offending and suggest that a perspective on a broad

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range of behavioral problems can be fruitful. The findings are discussed with regard to other studies on latent group-based modeling, non-statistical taxonomies, and practical applications.

Introduction

Prospective longitudinal studies enable the analysis of interindividual differences in intraindividual change and are therefore the preferred research design in developmental psychology (McCartney, Burchinal, & Bub 2006; Nesselroade & Baltes 1979). This approach, also called developmental and life-course perspective, acknowledges the basic assumption that human behavior and its connected social context are changing over time. Due to progress in longitudinal studies and statistical methodology (e.g., growth curve modeling) life-course research became particularly important in the study of antisocial behavior and led to the field of “developmental and life-course criminology” (e.g., Boers, Lösel, & Remschmidt 2009a; Farrington 2002).

Since the 1990s, statistical tools such as latent group-based modeling or general growth mixture modeling (GGMM) have been successfully applied to longitudinal datasets to describe the number and shape of violence, aggression and delinquency trajectories (see Piquero, Farrington, & Blumstein 2007; Jennings & Reingle 2012). By using GGMM or related tools it is possible to find different groups with individual change curves leading to different developmental outcome in terms of antisocial behavior or delinquency. In an early study Nagin and Tremblay (1999) used the data of the Montréal Study to analyze trajectories of boys’ physical aggression, oppositional behavior, and hyperactivity from ages 6 to 15. Four developmental trajectories were identified for the three problem behaviors under study. The group sizes varied depending on the particular behavior: a *chronic problem trajectory* (4–6 %), a *high-level near-desister trajectory* (25–30 %), a *moderate-level desister trajectory* (45–52 %), and a *no problem trajectory* (17–25 %). D’Unger et al. (1998) analyzed the data of three renowned longitudinal studies: the Cambridge Study in Delinquent Development (Farrington et al. 2009), the Philadelphia Birth Cohort Study (Tracy et al. 1990) and the Racine Birth Cohorts Study (Shannon 1988). The data were used to detect different trajectories with regards to official police records. The British data suggested four different trajectories: *nonoffenders* (64 %) with almost zero police contacts, one *adolescence-peaked trajectory* (12.7 %), and two *chronic trajectories*, one on a low (9.9 %) and the other on a high level (13.4 %). The data from Philadelphia came up with five different groups: *nonoffenders* (60.8 %), *adolescence-peaked trajectories (low rate)* (8.6 %), *adolescence-peaked trajectories (high rate)* (1.0 %), *chronic offenders (low rate)* (21.3 %), and *chronic offenders (high rate)* (8.3 %). And the Racine data came up with four or five classes depending on the birth cohort: *nonoffenders* (1942: 34.6 %; 1945: 35.4 %, 1955: 44.5 %), *adolescence-peaked trajectories* (1942: 20.1 %; 1945: 39.8 % (low-rate), 19.4 % (high rate); 1955: 2.2 % (early onset),

15.4 % (late onset)), and *chronic offenders* (1942: 31.4 % (low rate), 8.8 % (high rate); 5.1 % (late onset); 1945: 5.4 %; 1955: 30.1 % (low rate), 7.8 % (high rate)).

Bushway et al. (2003) used self-reported data of the Rochester Youth Development Study (RYDS; Thornberry 1997). Seven groups were identified: *very low-level offenders* (38.6 %), *low-level offenders* (22.5 %), *late starters* (9.8 %), *intermittent offenders* (8.6 %), *bell-shaped desisters* (8.5 %), *slow uptake chronic offenders* (7.8 %), and *high-level chronic offenders* (4.2 %). Hoeve et al. (2008) analyzed self-reported delinquency and conviction rates of youth who participated in the youngest cohort of the Pittsburgh Youth Study (PYS; Loeber & Hay 1997). Development was followed through age 20 and five different groups were found: *non-delinquents* (27.2 %), *minor persisting* (27.6 %), *moderate desisting* (6.8 %), *serious persisting* (24.2 %), and *serious desisting* (14.3 %). Bongers et al. (2004) studied problem behavior in children and adolescents aged 4–18 years in the Netherlands and found three types of parent-reported development of aggressive behavior: a *near-zero trajectory* (71.0 %), a *low decreaser trajectory* (21.4 %), and a *high decreaser trajectory* (7.7 %). The high-level trajectory showed the highest probability for predicting adult DSM-IV disorders (Reef et al. 2011).

Although the vast majority of studies on developmental trajectories of antisocial behavior has been carried out in the Anglo-American context, there is also research on this topic in Germany: Reinecke (2006) analyzed the data from the panel study Crime in the Modern City (CRIMOC; Boers, Seddig, & Reinecke 2009b) to identify different classes of deviant and delinquent behavior (self-report). From nine data waves starting at age 13, three classes evolved: *Adolescents with almost no deviant or delinquent activities* (58.2 %), a *medium proportion of adolescents with a low increase of delinquency* (33.3 %), and a *small number with a larger growth starting on a higher level* (8.5 %).

Overall, these and other studies suggest that there are no consistent numbers and types of developmental trajectories of delinquency, violence and crime. The most common results support Moffitt's (1993) theory-driven typology of an early starting and relatively persistent development of antisocial behavior versus an adolescence-limited pathway. In addition, nearly all studies show a large group of youngsters who are low in antisocial behavior across all measurement points. A recent systematic review of studies on developmental trajectories points in the same direction (Jennings & Reingle, 2012). Depending on age, type of sample (e.g., high risk vs. normative), kind of problem behavior, mode of measurement, method of analysis, geographical context and other issues the results varied between two and seven trajectories, but three to five were most common. Jennings and Reingle (2012) made a number of suggestions for further progress in this field research. In addition to more research on the explanation of different pathways, the authors suggest more studies on broader topics of developmental psychopathology, different cultural contexts, and data from multiple informants.

The present study follows the latter proposals. We analyzed the data of the Erlangen-Nuremberg Development and Prevention Study (ENDPS; Lösel et al. 2009, 2013) with regard to different trajectories for the broad category of externalizing problems. ENDPS is based on a normative sample and is a combined

experimental and longitudinal study on child behavior covering a time period of approximately ten years. Social behavior was rated in standardized reports from multiple informants such as mothers, kindergarten educators, school teachers, and the youngsters themselves. Therefore, the ENDPS can provide information on prototypical developments of a broad range of problem behaviors in a European context that may be relatively less biased by specific outcome measurements. As this publication is embedded in a method-oriented volume, the following section contains details of our statistical model and analysis.

Overview of Statistical Models

From a statistical point of view, one can treat latent growth curve modeling as multi-level models with the repeatedly measured observed variables on the first level and the latent variable on the second level (cf. McArdle 1988, 2005; Stemmler & Petersen 2012). If the assumption does not hold, that the underlying modeling of the growth over time is valid for a homogeneous population under investigation, growth curve models with latent classes come into play, to explain the “unobserved heterogeneity” (Nagin 1999; Muthén & Shedden 1999). The mathematical generalizations were described in a book on “finite mixture models” by McLachlan and Peel (2000). Nagin (1999) was the first scholar to apply growth curve modeling for different classes in the field of criminology. Nagin called his approach *semi-parametric, group-based modeling approach*, whereas Muthén (2004) used the term *latent class growth modeling* to underline the fact that in this model the random coefficient of the growth curve was fixed to zero, indicating no within class variation. However, this model is a special case of the general growth mixture models (GGMM) which can be analyzed with MPLUS (Muthén & Muthén 2010) or the LAVAAN package (Rosseel 2012) of the R statistical programming environment (R Core Team 2015).

The traditional growth curve model is based on the following equation (cf. Reinecke 2006, 2012):

$$y_t = \lambda_{t1}\eta_1 + \lambda_{t2}\eta_2 + \epsilon_t \quad (1)$$

In this formula y_t are the observed variables measured at time t , which are determined by the two latent variables η_i representing the *level* and *slope* of the growth curve, and ϵ_t the residuals (see Fig. 1).

The coefficients of the level are usually fixed to the value 1.0, whereas the coefficient of the slope may represent either linear growth (i.e., $\lambda_{12} = 1$, $\lambda_{22} = 2 \dots \lambda_{t1} = t$) or any other combination, as long as the necessary coefficients are fixed. The equations for the latent variables are

$$\eta_{\text{level}} = \alpha_1 + \zeta_1 \quad (2a)$$

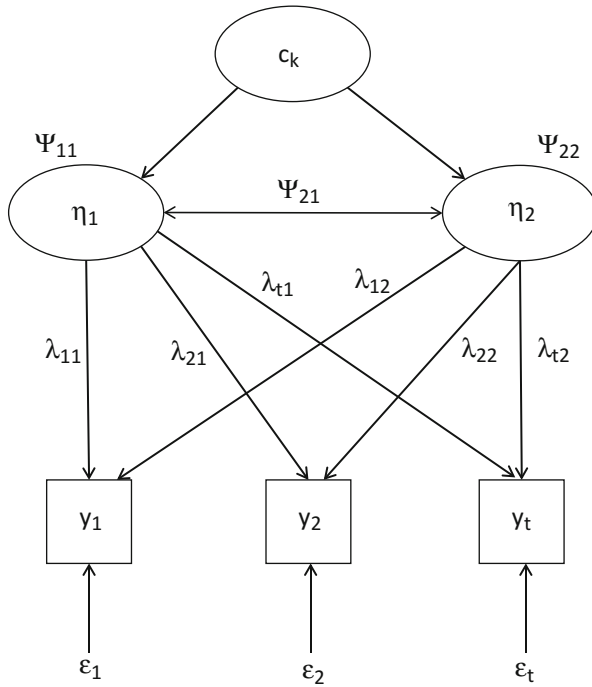


Fig. 1 A general growth mixture model (GGMM), which is basically a growth curve model with latent classes (c_k). *Note:* c_k are the different latent classes; η_i represents the latent variables for *level* and *slope*; the y_i are the observed variables for each measurement point; the ϵ_i are the residuals or error terms; the λ_i are the coefficients for the latent variables and ψ_i are the variance and covariances of *level* and *slope*

$$\eta_{\text{slope}} = \alpha_2 + \zeta_2 \tag{2b}$$

The above traditional growth curve can easily be extended to a conditional growth curve model if an exogenous variable, functioning as a predictor is included in the model. The extension is as follows:

$$\eta_m = \alpha_m + \Gamma \xi_n + \zeta_m \tag{3}$$

where the matrix Γ ($m \times n$) contains the regression coefficients of the exogenous variable ξ on the endogenous variables η_i . The variances and the covariance of the latent variables can be found in the psi-matrix (see Reinecke 2006, 2012):

$$\Psi = \begin{pmatrix} \psi_{11} & \\ \psi_{21} & \psi_{22} \end{pmatrix} \tag{4}$$

with ψ_{11} representing the variance of the level variable, ψ_{22} represents the variance of the slope variable, and ψ_{21} indicates the covariance between the two latent variables. If the growth model represents the different trajectories of different subpopulations, the statistical parameters vary across classes (see Fig. 1). According to Muthén (2004) such a general growth mixture model can be written as

$$y_{1k} = \lambda_{1tk}\eta_{1k} + \lambda_{2tk}\eta_{2k} + \epsilon_{tk} \quad (5a)$$

$$\eta_{1k} = \alpha_{1k} + \zeta_{1k} \quad (5b)$$

$$\eta_{2k} = \alpha_{2k} + \zeta_{2k} \quad (5c)$$

The variances of the η variables are estimated separately for each class, as well as their covariances. The parameters of GGMM can be estimated in MPLUS using the EM algorithm to obtain maximum-likelihood (ML) estimators (Dempster et al. 1977; Muthén & Shedden 1999). At the end, individuals are assigned a particular class based on their established posterior probabilities. This class membership may be used for further statistical analysis validating the obtained results of the GGMM; however there is controversy about this issue because class membership is based on probabilities and a pretended fixed class membership may overlook possible misclassifications due to error variance (Clarke & Muthen 2009).

There is no statistical test for the evaluation of the required number of necessary classes (Reinecke 2006, 2012), but there are useful statistical parameters such as the entropy measure E_k which varies between 0 and 1, with values close to 1 indicating a reasonable classification. And there are the Bayesian Information Criterion (BIC) or the adjusted BIC which are based on the maximum likelihood of the model. Of two comparing models the one with the lowest BIC or adjusted BIC is preferred. Finally, the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) compares the ratio of the likelihoods of two competing models, that is the (k-1)-classes model with k-classes model. The null hypothesis (H_0) states that the (k-1) model should be preferred. Therefore, significant or small p -values of the LMR-LRT are in support of the k-classes model. Another statistical parameter is the BRT (i.e., bootstrapped likelihood ratio test) which also compares the (k-1)-classes model with the k-classes model. The larger the likelihood the better the BRT. However, all statistical parameters are proxies that are used to select the best model, the final decision should also take theoretical issues into account.

In case of missing data MPLUS uses the full information maximum likelihood (FIML) estimator (Reinecke 2005). This estimator, which does not require Missing Completely at Random (MCAR) but Missing at Random (MAR), is well established in all currently available SEM programs. With a reasonably large sample size FIML produces unbiased parameter estimates.

Based on the abovementioned review of the life-course criminological literature we expected two groups with relatively stable levels of externalizing symptoms: those who are chronically high and those who are chronically low, with the latter group being larger. In addition, we envisioned groups with time-limited externalizing behavior and/or a later start of problems.

Method

Sample

The data were taken from the Erlangen-Nuremberg Prevention and Development Study (ENDPS; Lösel, Stemmler, Beelmann, & Jaursch 2005; Lösel, Stemmler, Jaursch, & Beelmann 2009; Lösel, Stemmler, & Bender 2013). The ENDPS is a combined prospective longitudinal and experimental prevention study with a multi-informant and multi-method approach. The original sample of the core study consisted of 675 kindergarten children (336 boys, 339 girls) from 609 families. The project is a longitudinal study that started at preschool age and is now containing seven waves of data collection. The sample was nearly representative of young families living in Erlangen and Nuremberg (Franconia). According to an index of the socioeconomic status (SES; Geißler 1994) which included income, education, profession, and housing conditions, 13.3 % of the families were lower class, 32.3 % were lower middle class, 30.6 % middle class, 15.4 % upper middle class, and 3.0 % upper class. Approximately 86 % of the parents were married at *Time 1*. The retention rates varied over time; in the most recent wave (nearly 10 years after the first one) approximately 90 % of the original sample participated (Lösel & Stemmler 2012; Stemmler & Lösel 2012).

For the analyses below, the data was structured according to age so that homogeneous age groups were assessed at the various measurement points. Data were collected when the study child was at the ages of 4 or 5, 6 or 7, 8 or 9, 10–12, and 13 or 14. Children were included if they had at least data on 3 out of the 5 measurement points. The data of the other two missing data points were imputed. Overall, the longitudinal sample contained $N = 541$ children. The cross-sectional sample sizes were as follows: $n = 525$ (4–5 years), $n = 424$ (6–7 years), $n = 422$ (8–9 years), $n = 486$ (10–12 years), and $n = 377$ (13–14 years).

Measures

The children's social behavior in kindergarten and at school was assessed by our German adaptations of the Social Behavior Questionnaire (SBQ; Tremblay et al. 1987; Tremblay et al. 1992). The SBQ is available in multiple versions. Here, kindergarten educators', school teachers', and mothers' ratings were used (Lösel, Beelmann, & Stemmler 2002). The content and format of the teacher's SBQ versions are identical and consist of 46 items. The mother's version has two additional items. The teacher's version item "stealing things" is divided for the mothers' version into "stealing things at home" and "stealing things outside home." Each item is rated on a 3-point scale ranging from "0" = *never/not true* to "2" = *almost always/true most of the time*. In the present study we only used items on externalizing behavior problems. Our *Externalizing Problems* scale was formed

of four primary scales: *Physical Aggression*, *Destroying Things/Delinquency*, *Indirect Aggression*, and *Hyperactivity/Attention Problems*. The reliabilities for the different informants were $\alpha = .89$ (preschool teachers/kindergarten educators), $\alpha = .91$ (school teachers), and $\alpha = .74$ (mothers).

To enhance the validity of measurement, at each wave the data from two informants were combined (mean of z -scores), that is weighing the teachers' and mothers' ratings equally. At preschool age we used the information from the mothers and kindergarten educators and at elementary school age the mothers' and school teachers' ratings. In secondary school we added the children's self-reports to the mothers' SBQ data, again using the mean ratings of the two informants. To assess externalizing behavior through the child's self-report we used the German version of the Strength and Difficulties Questionnaire (SDQ; Goodman 1999; German adaptation: Hölling, Erhart, Ravens-Sieber, & Schlack 2007). The items are answered on a 3-point scale ranging from "1" = *does not apply* to "3" = *does clearly apply*. The *Externalizing Scale* consists of five items. The reliability in our sample was rather low ($\alpha = .50$), but similar to the results from a nationwide German sample of the Robert-Koch Institute (Hölling et al. 2007). The mothers' SBQ ratings and the children's SDQ ratings were combined by averaging z -scores.

Results

Linear and quadratic latent class growth analyses with an increasing number of classes were tested. MPLUS, version 6, was used (Muthén & Muthén 2010). Models with within-class variation as well as with no-within-class variations were analyzed. Hundred random sets of starting values were generated in the initial stage and ten optimizations were carried out. The OPTSEED option was applied to specify the random seed that has been found to result in the highest log-likelihood in the previous analyses (Muthén & Muthén 2010). The fit of different latent classes ranging between one and six can be taken from Table 1. The statistical results suggest a linear GGMM of five classes according to Nagin (1999) with no-within-class variation. Here, a $BIC = 4051.39$ and an $adj. BIC = 3991.02$ were obtained. The $LMT-LRT$ suggested that compared to a $k-1 = 4$ -class solution the five-class solution should be preferred ($LMR-LRT = 79.75$, $p = .08$). The corresponding BRT generated the smallest value ($BRT = 83.97$) of all solutions with a likelihood ratio $LRT = -2007.89$. The smallest BIC and $adj. BIC$ were found for the six-classes model, but there were very small classes ($n < 10$) and the $LMT-LRT$ and the BRT revealed a lesser fit (Table 1).

The five classes represent different developmental trajectories from childhood to adolescence. Figure 1 depicts the different developmental trends. Squares indicate the "observed" means and triangles the estimated means. The upper dashed-dotted lines are the "*high-chronics*" (2.4 %; $n = 13$), who are receiving the highest values in externalizing behavior from childhood on up to adolescence. The opposite class are the "*low-chronics*" (dashed lines; 58.8 %; $n = 317$) who are low on externalizing

Table 1 Results of the general growth mixture models (GGMM) with different classes

Test	1 class	2 classes	3 classes	4 classes	5 classes	6 classes
BIC	5107.10	4353.58	4192.29	4116.48	4051.39	4021.67
Adjusted BIC	5084.88	4321.84	4151.02	4065.69	3991.02	3951.83
LMR-LRT	—	733.54	171.11	89.93	79.75	129.16
p-value	—	0.00	0.15	0.27	0.08	0.27
Likelihood	—	−2531.52	−2145.33	−2055.24	−2007.89	−2007.89
BRT	—	772.39	180.18	94.69	83.97	132.58
p-value	—	0.00	1.00	1.00	1.00	1.00
Class Sizes	541 (100)	435 (80.4)	375 (69.3)	346 (64.0)	317 (58.6)	315 (58.2)
N (%)		106 (19.6)	127 (23.5)	116 (21.4)	121 (22.4)	115 (21.2)
			39 (7.2)	48 (8.9)	47 (8.7)	44 (8.1)
				31 (5.7)	43 (7.9)	30 (5.5)
					13 (2.4)	29 (5.3)
						8 (1.5)

BIC Bayesian Information Criterion, LMR-LRT Lo-Mendell-Rubin likelihood ratio test, N = 541, BRT Bootstrapped likelihood ratio test

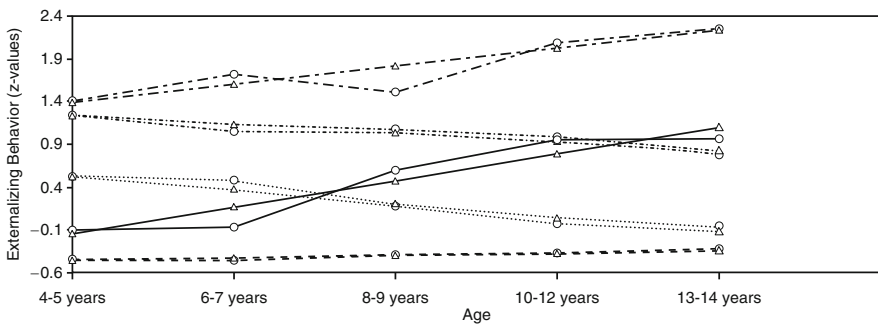


Fig. 2 Results of the general growth mixture model (GGMM) resulting in five developmental trajectories. *Note:* The y-axis displays the values for “Externalizing Behavior,” and all values were z-transformed. The x-axis shows the age of the juveniles at each measurement point. The squares represent “observed” means and the triangles “estimated” means. The upper dashed-dotted lines are the “high-chronics” (2.4 % of the sample), the dashed-dot-dotted lines are the “high-reducers” (7.9 %), the dotted lines are the “medium-reducers” (22.4 %), the ascending black lines are the “late-starters-medium” (8.7 %), and the dashed lines represent the “low-chronic” (58.6 %)

behavior throughout the years; including the majority of the sample. The dashed-dot-dotted lines are the “high-reducers” (7.9 %; n = 43) who start out high in childhood, but who reduce their externalizing behavior monotonically over time. By adolescence they are passed by the “late-starters-medium” (ascending black lines; 8.7 %; n = 47). Finally, the dotted lines show the trends of the “medium-reducers” (22.4 %; n = 121) who include about one-quarter of the sample. Their externalizing is medium high in kindergarten but decreases linearly up to adolescence (Fig. 2).

Discussion

Prospective longitudinal studies on problem behavior have a number of advantages (Loeber & Farrington 1994): They allow the study of the natural history of the development of problems such as onset, increase, decrease and termination. Based on individual data they enable the study of trajectories or pathways. A pathway is defined as “when a group of individuals experience a behavioral development that is distinct from the behavioral development of another group of individuals” (p. 890; Loeber & Farrington 1994). The identification of distinctive groups of trajectories enables one to estimate the proportion of the population following each trajectory group and to relate group membership probability to personal and social characteristics. Valid distinctions of developmental pathways can guide policy, e.g., with regard to risk-based early prevention programs (Farrington & Welsh 2007; Lösel et al. 2013). Loeber and Farrington (1994) also postulate that the best studies should rely on multiple informants. This is in accordance with numerous findings that showed rather low agreement between different informants from different social contexts (e.g., Achenbach 2006; Lösel 2002).

This research meets the abovementioned criteria. We adopted a developmental and life-course perspective by using the data of the Erlangen-Nuremberg Development and Prevention Study (ENDPS). We applied general growth mixture modeling (GGMM) to data from early childhood to adolescence, covering a 10-year period, on externalizing behavior problems rated at each measurement point by two different informants (kindergarten educators, mothers, school teachers, and self-report). The results suggested a five-class solution representing five different developmental trajectories.

Although our study contained data on a broad range of externalizing symptoms and a community sample of boys and girls from Germany the results were relatively similar to Anglo-American studies that used Nagin’s (1999) approach on *semiparametric group-based modeling*. As mentioned in the introduction, most studies showed between three and five classes depending on the type of outcome measures and samples used (Jennings & Reingle 2012). The small group of “high-chronics” and the largest group of “low-chronics” (no problems at all times) are in accordance with the well-replicated trajectories of delinquency, aggression, and violence (Jennings & Reingle 2012). The group of “high-reducers” confirms that not all children who exhibit early antisocial behavior enter on a persistent pathway. In contrast, various international studies have shown that a half or more recover within a short period of time (e.g., Moffitt et al. 1996; Nagin & Tremblay 1999; Werner & Smith 1992). Even in the presence of various risk factors abstaining or early desistance from problem behavior seems to be more the rule than an exception (Lösel & Bender 2003; Lösel & Farrington 2012). Our fourth trajectory of “late-starters-medium” may indicate an early phase of the adolescent-limited pathway that has been found in studies that covered the whole range of youth and young adulthood (e.g., Moffitt et al. 2002). Further waves of the ENDPS may show whether the increase of externalizing problems continues until late adolescence and then be

followed by a decrease. The fifth trajectory we found in our study is insofar plausible as it shows a moderate level of behavioral problems that decreased from early childhood to youth. These “medium-reducers” show a similar trend as the “high-reducers,” but are a larger group that decreases from a more normative lower level of externalizing problems. Both pathways may indicate positive influences of cognitive competences, self-control, and social skills that reduce physical aggression and other antisocial behavior from early childhood onwards (e.g., Tremblay et al. 2004).

Overall, our findings fit well into the international criminological literature. However, there seems to be a difference with regard to the size of the group with intensive and persistent problem behavior. Whereas in criminological trajectory studies often approximately 5 % of a cohort belonged to this category, in our study only 2.4 % belonged to this group. This lower prevalence may have been partially due to the comparatively young age when our sample was first assessed. In addition, less serious problems of externalizing behavior in a “normal” community sample may be more temporary and thus not lead to a larger group with high problem stability. Taking together the “high-chronics” and the “high-reducers” the respective proportion was about 10 %. This is within the range of point prevalence rates for externalizing child behavior in Germany (e.g., Hölling et al. 2007).

One should also mention that our study contained both boys and girls. As boys show more externalizing problems than girls the relatively small size of the “high-chronics” group is plausible. Because we investigated a nearly representative sample of the local area we included both sexes in the trajectory analysis. As boys show more externalizing problems than girls (see Lösel & Stemmler 2012; Moffitt, Caspi, Rutter, & Silva 2001; Moretti & Odgers 2002), mixed-gender studies on this issue may contain problems. However, different prevalence rates do not necessarily imply that there are different risk variables and developmental processes. Although gender is a sound predictor of delinquency and offending (Ryder, Gordon, & Bulger 2009), most risk variables for boys and girls seem to be similar (see Moffitt et al. 2001; Silverthorne & Frick 1999). Boys simply show more risks for externalizing problems and girls may also benefit from more protective factors and mechanisms (e.g., Lösel & Bender 2003; Lösel, Stemmler, & Bender 2013; Werner & Smith 2001).

In sum, the results of our study are consistent with international research that concentrated on more specific forms of antisocial behavior. Addressing a broad range of externalizing problems bears the advantage of a relatively sensitive detection of early needs for intervention and prevention. In the ENDPS we found encouraging effect sizes in predictive validity with Odds Ratios of up to 10 (Wallner, Lösel, Stemmler & Corrado, submitted). More detailed analyses on the prediction of trajectories are in progress.

However, the present study underlines the methodological progress due to the invention of GGMM. It allows the empirical and statistical driven search and identification of different developmental pathways that overcomes more or less arbitrary definitions of groups. For example, Moffitt (1993) defined boys as “life-course persistent antisocial” if they had above average scores (by at least one standard deviation) on a scale of antisocial behavior. Elevated scores by three raters

(parents, teachers, and self) were required at each of seven biennial assessments from age 3 to 15. However, for various reasons, the algorithm had to be changed later to at least three elevated scores out of the 5 assessments from ages 5 to 11 years (Moffitt et al. 2002). In another high-quality study Elliott and Huizinga (1980) defined youngsters as *high delinquents* if they had more than 12 crimes per year, as *exploratory delinquents* if they had equal or less than five crimes per year. Such a priori definitions always involve some kind of arbitrariness. In our view, such group definitions are well justified as long as they are to some degree theory driven. It is encouraging that such original groupings were supported by advanced statistical analyses (Nagin, Farrington, & Moffitt 1995). Insofar, GGMM has provided a tremendous progress in finding the most adequate number of groups or pathways leaving behind scientific capriciousness.

However, in spite of the convergent validity of our results with studies from North America one must acknowledge various limits. First, although the algorithm for the selection of different trajectories is fully objective, the final solution still required some subjective decisions (i.e., the exclusion of a pathway with very small group size). Second, GGMM leads to pathways of *relative* and not *absolute* homogeneity in development; that is, one must assume individual cases in each trajectory that are rather similar to some cases in another pathway. Third, GGMM provides a descriptive developmental grouping of a specific data set that requires cross validation. Fourth, it needs to be emphasized that the labeling of the different groups is data-driven and not based on theoretically or clinically relevant distinctions. For example, the children on the “high-chronic” pathway in our community sample may still differ in many characteristics from a persistent group of offenders in a high-risk sample. This points to a general problem with GGMM. The question is whether the identified latent classes are real existing subpopulations or just different statistically generated groups with rather general labels made up by researchers. Therefore, further investigation of differential predictors of various developmental pathways is an important task for our own and other future research. If one is not interested in finding discrete latent classes or if one does not assume the existence of subpopulations one could use the so-called heterogeneous growth curve modeling (HGM; Brandt & Klein *in press*). HGM models growth curves while using covariates like gender or school type to explain the unobserved heterogeneity in the slope variance. Further limits of the abovementioned GGMM are the use of categorical variables or extremely non-normal data (for solutions see Bauer & Curran 2004).

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