**Competence Development of High Achievers Within the Highest Track in German
Secondary School: Evidence for Matthew Effects or Compensation?**

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1. Introduction

Children enter school with different skills and levels of prior knowledge. For teachers, this heterogeneity represents a challenge, because they are expected to support all students realize their full potential while considering that these differences in prior knowledge and skills have an impact on their further learning and academic development. Teachers facing the dilemma of how to distribute their resources might endorse the opinion that high achievers need no specialized promotion because they are already advantaged and will continue to succeed anyway (Bannister 2016; Brighton, Hertberg, Moon, Tomlinson, & Callahan, 2005). However, to date, it is unclear whether such students continually outperform other students or whether their advantages level off across the school career. Thus, research should investigate, in how far schools currently succeed in promoting the advancement of high achievers compared to other students.

Until now, the academic development of students at different levels of initial achievement has often been studied from the viewpoint of cumulative advantage (e.g. Baumert, Nagy, & Lehmann, 2012; Cunningham & Stanovich, 1997; Shaywitz, Holford, Holahan, Fletcher, Stuebing, Francis, & Shaywitz, 1995; Walberg & Tsai, 1983). This perspective stresses that success facilitates further success, and small advantages in an early stage of a growth process grow progressively larger (DiPrete & Eirich, 2006). For the academic domain, it suggests that children with a head start in a certain subject or domain will continually make more progress than their peers, given the same instruction. This process is also referred to as Matthew effect (Ceci & Papierno, 2004; for a discussion on the usage of the term, see Zuckerman, 2011).

To our knowledge, empirical research on the Matthew effect has mostly focused on reading in primary school contexts. Research focusing on secondary school or research looking

at different subjects is more scarce. Specifically, research on achievement gaps in secondary school mostly looked at between track differences in learning gains (e.g. Becker et al., 2014; Dockx, de Fraine, & Vandecandelaere, 2018; Kulik & Kulik, 1982; Pfof & Artelt, 2013). In contrast, this paper will describe differences in academic growth *between* high achievers and their peers *within* the highest track of secondary school.

Therefore, with the current study, we aimed to extend previous research by clarifying whether either the cumulative advantage hypothesis (i.e., the Matthew effect) or the compensation hypothesis, which predicts that achievement gaps would decrease over time, can be substantiated for upper track secondary school students' academic development in reading and mathematics or whether neither of them apply and parallel development for different achievement groups can be observed. In particular, we were interested in determining whether reading and mathematics would show similar result patterns. By using a longitudinal German data set with yearly measures from Grades 5 to 9 in reading and from Grades 5 to 8 in mathematics, we covered an important phase in students' academic and personal development starting right after their transition to secondary school.

1.1. Academic achievement gap: Cumulative advantage versus compensation

When studying differences in growth between students, one of two competing hypotheses can be put forward: the cumulative advantage (or Matthew effect) hypothesis or the compensation hypothesis. Before examining empirical evidence, in the following, the assumptions behind either of the two are being discussed.

The concept of cumulative advantage with its different interpretations has been specified by DiPrete and Eirich (2006) and Baumert et al. (2012). They have distinguished between *status dependent processes of cumulative advantage* and *path dependent processes of cumulative*

advantage. While the former are the result of the differential impact of individual characteristics (e.g., socioeconomic status, race, gender, cognitive abilities) on learning gains and lead to increasing differences between status groups, the latter occur solely based on previous achievement level which enables high achievers to learn more from the same instruction. These path dependent processes of cumulative advantage are the focus of the current paper. It should be possible to find empirical evidence for them in patterns of diverging cohort trajectories between initial high achievers and others.

A domain specific model predicting Matthew effects in reading has been developed by Stanovich (1986). He assumed that the accelerated pace of reading development in high achievers would be mediated by higher reading motivation and reading practice in this group. This mechanism is assumed to work in particular in the beginning of reading skill acquisition and has been studied extensively in primary school (Pfof, Hattie, Dörfler, & Artelt., 2014).

Whereas such an explicit model of differential academic development for different achievement groups does not exist for mathematics, the idea of Matthew effects in mathematics is very plausible if the cumulative nature of mathematical skills is acknowledged such that from basic to more advanced skills, each step of learning is based on prior knowledge and skills. Consequently, the assumption of cumulative advantage has been suggested not only for reading but also for mathematics, thus implying that children who initially show higher achievement in mathematics also show higher rates of growth than children with less prior knowledge in mathematics (Claessens & Engel, 2013; Duncan et al., 2007).

Whereas research on the Matthew effect has so far been mainly concerned with primary school development, the self-reinforcing mechanism resulting in cumulative advantage could in principle also be valid for secondary school. That is, higher achievement might lead to the more

(effective) use of learning opportunities and to faster rates of learning throughout students' school careers.

However, for most skills taught in school, the acceleration of student learning may not subsist. It has been argued that some skills have a natural ceiling that is reached earlier by some students, and then no or only limited further skill advancement can occur (Baumert et al., 2012). Thus, Matthew effects might not reflect genuinely different rates of growth but merely different timing in the onset of a developmental process and might be followed by compensation processes when "late bloomers" catch up (developmental-lag model; Pfoest et al., 2014). As a result, secondary school might also be a time when students with a lower ability level close the achievement gap between themselves and others. This could be seen in compensatory development.

However, additional factors that are not present in primary school affect academic development in secondary school and may increase or decrease the Matthew effect. In Germany, where the current study was located, students enter into an institutionally tracked education system after primary school. The different tracks provide different learning environments with different curricula, different teaching cultures, and different teacher training study programs, but also with different compositions of students (Baumert, Stanat, & Watermann, 2006; Pfoest & Artelt, 2013). Academic development in secondary school has mostly been studied either with a focus on the effects of tracking in general or on the effects of ability grouping (Baumert, Becker, Neumann, & Nikolova, 2009; Kulik & Kulik, 1982; Maaz, Trautwein, Lüdtke, & Baumert, 2008; Pfoest & Artelt, 2013; Pfoest, Karing, Lorenz, & Artelt, 2010). However, so far no research has focused on the difference between high achievers and other students within the highest track of secondary school.

Various mechanisms within the highest track of secondary school could lead to a continuing pattern of cumulative advantage in initial high achievers. Among these are effects of instructional design in high track schools and compositional effects, which we elaborate on in the following.

1.1.1. Instruction and differences in achievement growth

The teaching strategies employed in high-track schools are characterized by cognitively activating and demanding instruction methods (Kunter et al., 2005; Slavin, 1990). However, the effectiveness of different teaching strategies has been found to vary with students' ability level (Caro, Lenkeit, & Kyriakides, 2016; Snow & Lohman, 1984). Instructional design in the high-track schools might thereby be more tailored to higher aptitude students, for example, such that lessons are less tightly structured or less feedback is given (Baumert, Maaz, Stanat, & Watermann, 2009; Fyfe, Rittle-Johnson, & DeCaro, 2012; Jennek, Gronostaj, & Vock, 2019). This learning environment might be especially well suited to high achievers' cognitive and motivational preconditions, possibly leading to an acceleration of their future development compared with their peers, thus supporting the Matthew effect hypothesis.

But, although frequently promoted, differentiation practices, which should enable all students to progress at high rates, seem to be rather rare in classroom practice (Archambault et al., 1993, Tomlinson et al., 2003). Where differentiation is employed, it is often implemented with a focus on students who are struggling to learn, rather than on more advanced students (Brighton, Hertberg, Moon, Tomlinson & Callahan, 2005; Plucker & Callahan, 2014). This might be due to limited resources or skills of teachers to implement differentiated teaching and to provide appropriately challenging tasks for high achievers (Brighton et al., 2005). But it might also be due to teacher beliefs and attitudes (McCoach & Siegle, 2007; Tomlinson et al., 2003).

Thus, higher gains for lower achieving students or a pattern of compensation may result from teachers aiming for homogeneity in their classrooms and devoting more time to lower achieving students.

1.1.2. Classroom composition and differences in achievement growth

After primary school, the most advanced students have the opportunity to transfer to the highest track secondary schools. Thus, the achievement standard within the new classes is raised compared to primary school. The opportunity to compare their abilities and achievement to students who match them more closely has been found to be a motivational factor for those performing at the highest levels (Li & Adamson, 1992; Phillips & Lindsay, 2006; Udvari & Schneider, 2000). It might stimulate them to accelerate the pace of their academic development and result in cumulative advantage.

But, again, there are aspects related to class composition which favor lower achievers within a higher achieving class. In particular, the composition of the student body in high-track schools has been found to be an effective resource for academic development (Dar & Resh, 1986), even though this often comes at the price of a lowered academic self-concept as a result of upward social comparisons (Trautwein, Lüdtke, Marsh, & Nagy, 2009). A number of studies have shown that the positive impact of being in a high-achieving class on children's academic development is higher for children with lower achievement levels (Dar & Resh, 1986; Kiss, 2013; Linchevski & Kutscher, 1998; Ma, 2005). However, whether this effect offsets the positive effect of higher initial competencies on subsequent performance and can therefore cause compensation effects is questionable (Kiss, 2013).

Thus, two central aspects students are confronted with after transitioning to secondary school—compositional effects as well as teaching methods within the highest track—might favor

high achievers or low achievers and no clear prediction can be made as to whether a pattern of growing differences or a compensatory pattern can be expected.

1.2. Previous research findings

Prior research on path-dependent processes of cumulative advantage in reading has produced mixed results. In their meta-analysis of Matthew effects in reading development in primary school, Pfoth et al. (2014) concluded: “We did not find strong support for the general validity of a pattern of widening achievement differences or for a pattern of decreasing achievement differences in reading” (Pfoth et al., 2014, p. 203). However, this meta-analysis, like many studies in the field focused on primary school contexts. Some studies also included the later years of primary school, that is, Grades 4 to 6. Examining these studies’ results for the later years, one can either use intercept-slope correlations of growth curve models or calculate effect sizes of differences in reading growth between high and low achieving groups. Intercept-slope correlations in reading were between $r = -.07$ and $r = -.63$ (Baumert et al., 2012; Morgan, Farkas & Wu, 2011; Shin, Davison, Long, Chan & Heistad, 2013). Effect sizes of between-group differences in growth amounted to between $d = -0.01$ and $d = -0.21$ (Aarnoutse, van Leeuwe, Voeten & Oud, 2001; Rambo-Hernandez & McCoach, 2015). All of these results were in favor of lower achieving students. On the contrary, Scammacca, Fall, Capin, Roberts & Swanson (2019) reported higher growth rates of high achievers compared to low achievers, with an effect-size difference of $d = 0.11$ across Grade 5. However, these studies differed in which groups they compared: While Rambo-Hernandez and McCoach (2015) compared the top 2 % with an average achieving group (16th-84th percentile), Aarnoutse and von Leeuwe (2000) and Aarnoutse et al. (2001) split the sample to form a group of 30 % lower achieving and 70 % higher achieving students and Scammacca et al. (2019) compared the lowest and the highest quartile.

For the development of mathematical skills, less research has been conducted, but studies comparing growth rates between groups of children with different early mathematics skills have also revealed mixed results. In their review, Nelson and Powell (2018) point out, that most studies on the longitudinal development of different ability students in math are conducted in primary school. Those studies that go beyond third grade have mostly found evidence for a Matthew effect (Morgan, Farkas & Wu, 2009; Morgan, et al., 2011; Lu, 2016), with intercept-slope correlations between $r = .36$ and $r = .46$. Shin et al. (2013) showed intercept-slope correlations as low as $r = .10$ across Grades 4-7 and Ma (2005) reported very high intercept-slope correlations between $r = .55$ and $r = .99$. An exception is Scammacca (2019): In this study, the difference in growth between high achievers (top 25%) and low achievers (bottom 25%) across Grade 5 was $d = -0.26$ in favor of lower achievers. Thus, while for reading, most studies have found compensation effects, studies on the development of mathematic skills predominantly found Matthew effects.

What is noteworthy about the previous research in both domains is the dominant focus on trajectories of poorly performing or low ability students (Aarnoutse & van Leeuwe, 2000; Claessens & Engel, 2013; Jordan, Hanich, & Kaplan, 2003; Kühn, Sachse, & Suchodoletz, 2015; Pfof et al., 2012; Shin et al., 2013; Skibbe et al., 2008) and the lack of studies focusing on high achievers (for an exception, see Rambo-Hernandez & McCoach, 2015).

1.3. The present study

Our study focuses on the question of who learns more in the highest track of secondary school—initial high achievers or their relatively lower achieving peers. Reviewing the current literature on the topic, we identified certain gaps we are aiming to address. Firstly, the vast majority of studies have investigated academic development of different achievement groups in

primary school contexts and secondary school has less often been the period under investigation. Secondly, when previous studies contrasted different achievement groups, they mostly focused on low-achieving children (Francis et al., 1996; Jordan et al., 2003; Pfof et al., 2012; Shin et al., 2013; Skibbe et al., 2008). High achievers have been explicitly considered in few studies (for example, Rambo-Hernandez & McCoach, 2015). Thirdly, academic development in secondary school in general and the development of the achievement gap between high achievers and others might be nonlinear. But, nonlinear trajectories have not been considered in many studies (see Baumert et al., 2012; Pfof et al., 2012; Francis, Shaywitz, Stuebing, Shaywitz, & Fletcher, 1996, Shin et al., 2013, for exceptions). Furthermore, not many any studies have analyzed both reading and mathematics skills simultaneously, making results comparable between different domains (see Baumert et al., 2012, for an exception).

Thus, our study aimed to examine learning trajectories in reading and mathematics in secondary school and to evaluate the evidence for differential growth patterns of initially high-achieving students compared with other students. Based on the theoretical assumptions and the previous research described above, three conflicting hypotheses can be formulated regarding differences between high achievers and their peers in reading and mathematics: First, the trajectory of high achievers compared to their peers may be characterized by a pattern of cumulative advantage (i.e., steeper growth for initially high-achieving students compared with students with lower achievement) as a result of their higher prior skills and knowledge as well as the more stimulating learning environment in secondary school (H1.a). On the contrary, other students might also catch up— because the compositional effect of being in a high-achieving class favors them, because teachers might invest more resources in them, or simply because they follow higher achievers on a non-linear trajectory —leading to a pattern of compensation (H1.b).

Finally, these processes might cancel each other out, leading to parallel achievement trajectories (H1.c). Given the conflicting previous evidence, we did not a priori favor one of these hypotheses.

Second, we aimed to determine whether growth rates (and group differences in growth rates) change over time, indicating nonlinear developments. Based on the previous research (Baumert et al., 2012; Pfoest et al., 2012; Francis et al., 1996; Shin et al., 2013), we expected that the academic development of students in reading and mathematics follows a non-linear shape across secondary school. Specifically, we expected the growth rates of high achievers and their peers to show the largest differences in the early years of secondary school (H2). During this time, within the newly formed learning groups social and cognitive adjustment processes take place. Moreover, teachers might strive for a more homogeneous level of knowledge and skills in their new classes.

Third, we were interested in whether development in reading and mathematics would show similar patterns. While there are some processes which would affect development in both subjects simultaneously (newly formed classes in fifth grade, deceleration of academic development in general), others might be subject specific (nature of the skills to be learned, learning opportunities inside and outside of school). Because of the cumulative structure of the mathematics curriculum, the increasing complexity of the learning content and the confinement of mathematics learning to the mathematics classroom, while reading practice is almost ubiquitous (in different school subjects as well as outside school), we expected a larger difference in trajectories in favor of the high achievers in mathematics compared to reading (H3).

We used a German panel study that collected achievement data in reading and mathematics at five and four measurement points, respectively, with the first measurement point

taking place at the beginning of secondary school. We addressed our research questions in the structural equation modeling framework by modeling paths of academic development using latent growth curve models and applied different modeling approaches to check our results for robustness. Further, we paid special attention to the issues of measurement invariance across measurement points by linking the scales longitudinally.

2. Method

2.1. Study design

We used data from the BiKS study (Bildungsprozesse, Kompetenzentwicklung und Formation von Selektionsentscheidungen im Vorschul- und Schulalter [Educational processes, competence development and selection decisions in preschool and school age] (Artelt, Blossfeld, Faust, Roßbach, & Weinert, 2013), which was conducted between 2006 and 2014 in the two German federal states of Bavaria and Hesse. In this study, approximately 2,400 children were followed from third grade to ninth grade. In Bavaria and Hesse, as in most German federal states, primary school comprises the first four years of schooling, after which children transfer to the tracked secondary school system (for a brief overview of the German tracking system, see Supplement A). In the study, students were tested annually with a selection of ability and achievement tests, and students, teachers, and parents also answered questionnaires. In order to test school children, researchers had to obtain approval by the relevant Ministries of Education, which entails ethical approval as well as compliance with data protection guidelines. A detailed description of the study can be found in Lorenz, Schmitt, Lehl, Mudiappa, and Rossbach (2013).

2.2. Analysis sample

To address the question of whether patterns of cumulative advantage for high-achieving students can be found in high-track secondary school either in reading or in mathematics, we

used data from the beginning of secondary school in fifth grade to ninth grade and restricted our sample to students attending *Gymnasium* (i.e., the highest secondary school track in Germany). About 53% of the students in the total sample attended this school type. We excluded students who had repeated a grade level because their learning trajectories necessarily differed. This left us with a total sample of 1,010 students in our analysis sample. At the first measurement occasion, 928 students participated in reading, and 892 participated in mathematics. As can be seen in Table 1, the number of participating students decreased substantially over the course of the study. Our approach for dealing with missing data is described in Section 2.4 below. Students' demographic characteristics in Grade 5 are given in Table 2.

High achievers were operationally defined as children scoring at least 1 SD above the total sample mean at the first measurement occasion. Thus, 12.5% of the students in Grade 5 were initially high achievers in reading, and 15.6% were initially high achievers in mathematics. For high achievers, there is currently no standard definition in the literature. In his Differentiated Model of Giftedness and Talent 2.0, Gagné (2009) called the top 10% of achievers “(mildly) talented.” In international large-scale assessments, students are grouped in proficiency levels. In the previous PISA cycle, 11.7% of German students in reading and 12.9% in mathematics scored in the two highest proficiency levels (OECD, 2016). By choosing a cut-off value of 1 SD above the mean, we aimed to describe a comparable group of high achieving students which is of practical significance. Our analysis decision was made prior to analyzing the data, but as a validity check, we re-analyzed the data using different cut-offs and found the same pattern of results. These additional analyses are detailed in supplement B.

2.3. Instruments

The *reading assessments* comprised three to five short texts with related multiple-choice

items. The test was developed by the BiKS research group with additional items of increasing difficulty added in each wave (DFG-Forscherguppe "Bildungsprozesse, Kompetenzentwicklung und Selektionsentscheidungen im Vorschul- und Schulalter" [BiKS], n.d.; Pfof, Dörfner, & Artelt, 2013). Between 25 and 43 items were administered during each wave of measurement and all reliabilities were acceptable (Cronbach's $\alpha > .74$).

The *mathematics assessments* were compiled from items from existing tests (DEMAT5+; Marx & Opitz-Karig, 2005, DEMAT6+; Götz, Lingel, & Schneider, 2013, PALMA; Pekrun et al., 2003, TIMSS; Baumert et al., 1998). The item content covered story problems, arithmetic, and geometry. The test forms used in the consecutive waves of measurement comprised between 29 and 44 items, and internal consistencies ranged from $\alpha = .75$ to $\alpha = .81$ in all waves. In contrast to reading, mathematics skills were not assessed in Grade 9. Thus, only four points of measurement were available. All subsequent waves of measurement in both reading and mathematics shared a set of common items—so-called anchor items—so that vertical scaling methods could be applied (Kolen & Brennan, 2014).

2.4. Data analysis strategy

2.4.1. IRT scaling and equating

To obtain ability estimates that were comparable between measurement occasions, we used the item response theory framework (IRT; Embretson & Reise, 2000) and equated the tests across all waves of measurement using the fixed item parameter calibration method (Kim, 2006; Kolen & Brennan, 2014; von Davier & von Davier, 2004). Thus, each wave was calibrated by fixing the anchor items to the estimated values of the previous wave (for a discussion on the comparability of achievement scores, see Protopapas, Parrila, & Simos, 2016). To ensure parameter invariance, we used an approach often recommended in the literature (Fischer, 1995)

and excluded items that functioned differently between adjacent waves (i.e., items that showed item parameter drift) from the pool of anchor items. To this end, we first tested for differential item functioning (DIF) in the anchor items between two measurement occasions. We did this by scaling a test that contained only the anchor items and by treating students at the first measurement occasion as one group and students at the following measurement as the second group. DIF between the two groups was estimated and evaluated according to the ETS classification scheme (Zieky, 1993). Only items that showed no significant DIF were included as anchor items. Sixteen and eight linking items had to be excluded in reading and mathematics, respectively, leaving a minimum of four and a maximum of 20 items to be used to link two subsequent waves. Based on these selected anchor items, the achievement tests were scaled separately using a one-parameter logistic IRT model with the software ConQuest 2.0 (Wu, Adams, Wilson, & Haldane, 2007) in combination with the R package eatModel (R Core Team, 2018; Weirich & Hecht, 2018). Weighted Likelihood Estimates (WLEs; Warm, 1989) were used as estimates of student ability. In accordance with Pfoest et al. (2012), missing values for the first measurement occasion were imputed using the EM Algorithm (Dempster, Laird, & Rubin, 1977) as implemented in the R-package dlsem (Magrini, 2016). This approach ensured that all children could be placed in either the group of high achievers or in the group of other students. For reading, data had to be imputed for 82 students, whereas for mathematics, data had to be imputed for 118 students. These WLE scores were used in all of the following analyses, which were carried out in the structural equation modeling framework.

2.4.2. Structural equation models

Latent growth curve models (LGCs) are one common approach that can be applied to identify Matthew effects, especially when scales can be linked across waves (Bast & Reitsma,

1997). In linear LGCMs, trajectories of construct development across several measurement points are described by (a) the initial level (intercept) and (b) a linear increase or decrease (slope). Both the intercept and the slope are allowed to vary across students. If a process of cumulative advantage takes place, growth should be larger for higher achieving students than for other students (indicated by a higher slope estimate for this group). If, on the contrary, the data supports the compensation hypothesis, initial high achievers should show less growth in competencies than their lower achieving peers (indicated by a lower slope estimate for this group).

We first estimated one growth curve for all students across the measurement points (see Figure 1A, Model 1). We then tested for nonlinear development in achievement by additionally estimating a quadratic growth curve (see Figure 1A, Model 2). In a second step, we estimated separate growth curves for high achievers and others within a multigroup framework (Model 3). We compared these growth curves across the two groups of different attainment when they began secondary school. Estimating a two-group model also enabled us to investigate the average curves of the two groups visually and to test the model parameters (e.g., the mean of the slope factor) for equality. Third, we wanted to check whether the difference in growth between the two groups stemmed from a certain period of development, and therefore, we used a piecewise modeling approach (Chou, Yang, Pentz, & Hser, 2004). Within this model, separate linear terms were estimated for the first and the second part of the growth curve. This approach constitutes an alternative nonlinear model, and it thus allowed us to explicitly compare different segments of the growth curve between the two groups (see Figure 1B; Model 4). These steps were conducted for reading and mathematics separately.

The growth curve analyses were conducted in MPlus v 7.11 (Muthen & Muthen, 1998-

2011), and the *Full Information Maximum Likelihood* (FIML) method was used to estimate all models using the whole sample to best capture all relations between the variables that were analyzed. This model-based approach is considered superior to traditional approaches (e.g., listwise or pairwise deletion) because it offers unbiased parameter estimation under the Missing-at-Random (MAR) assumption and retains statistical power because all observations are used (Enders, 2010; Wothke, 2000). However, because of the considerable share of missing data after Wave 3, which was mainly related to the failure of parents to renew their informed consent to the study (Homuth, Schmitt, Lorenz, & Mann, 2017), we re-analyzed the data using a model accounting for data missing not at random (NMAR). These analyses and results are detailed in Supplement B.

3. Results

3.1. Descriptive statistics

Table 1 shows descriptive statistics for reading and mathematics achievement at each measurement point, as well as the stabilities (i.e., the autocorrelations) across all waves. As expected, mean reading and mathematics scores increased across the five or four points of measurement as the students progressed through secondary school. The total gains were 2.97 SDs based on the variance at Time 1 for reading and 1.95 SDs for mathematics. Stabilities were medium-sized, and the correlations between successive points of measurement were higher than they were between more distant points of measurement, thus showing the typical pattern for autocorrelations across time (Campbell & Kenny, 2003). The correlations between the first and last points of measurement were still $r_{r1-5} = .38$ and $r_{m1-4} = .45$ for reading and mathematics, respectively. These correlations indicate moderate rank-order stability in achievement but also substantial differences between students in skill development.

Finally, comparing raw growth rates of high achievers and other students across the time points, the differences were substantive, indicated by effect sizes ranging from $d = -1.08$ to $d = -1.40$ in reading and from $d = -.82$ to $d = -1.00$ in mathematics (see Table 3). These negative effect sizes indicate that, for example, high achievers' standardized reading gain across the first period of measurement was 1.15 units smaller than the other group's gain, and their increase in mathematics achievement was 0.82 standardized units smaller than the other groups' increase.

3.2. General patterns of academic development

3.2.1. Reading achievement

As already suggested by the descriptive statistics, the LGC in Model 1 estimated an increase in reading ability (Table 4). More specifically, the mean of the slope factor was 0.47—that is, on average, students' yearly achievement growth was equal to 0.47 units on the achievement metric at T1. The slope variance was also significantly greater than zero ($\sigma^2 = 0.02$, $p < .001$) indicating that students differed in their competence development. In order to determine whether the growth in reading followed a nonlinear pattern, a quadratic growth curve was estimated next (see Table 4). A significant negative quadratic growth factor of -0.06 indicated that growth in reading development was slowing down across secondary school. Introducing a quadratic growth factor helped increase the model fit slightly (see Table 5).

3.2.2. Mathematics achievement

Table 6 shows results for the first two models of mathematics development. Similar to reading, the slope of 0.54 ($p < 0.01$) with its significant variance showed that there was overall growth but also significant differences between individuals in growth. In mathematics, there was also a significant negative quadratic growth, indicating a slowing down of learning processes. The quadratic model showed an improved model fit compared to the model without the quadratic

term (see Table 5).

3.3. Testing for differential competence development using multigroup models

To examine the different achievement trajectories for students with high versus lower achievement more closely than only based on intercept-slope correlations, we estimated multigroup growth curve models. Because the first models indicated that growth proceeded in a nonlinear fashion (see Table 4, Model 2, and Table 6, Model 2), we also included a quadratic term in the multigroup models (Model 3). In addition, because the quadratic growth curve shows whether the linear and quadratic growth factors differ between groups, but is not as informative about the timing of differential development, we used piecewise growth curve modeling (Chou et al., 2014) in Model 4 to determine whether the difference in growth stemmed from a certain period of development. Inspecting the estimated and empirical mean curves in Model 3 for both reading and mathematics visually (see Figure 2), differences in growth between the two groups seemed to exist mainly in the early stages. Thus, we estimated a growth curve with two linear segments, one for the first period (Time 1-Time 2) and one for the time after (Figure 1B).

3.3.1. Reading Achievement

The results in Table 7 indicate that for children with initially high achievement, the linear and quadratic slope factors in Model 3 differed significantly from the other students. High achievers showed a smaller linear slope ($\Delta_{\text{lin}} = -0.50, p < .001$) and a nonsignificant quadratic growth factor that also differed from that of other students ($\Delta_{\text{qua}} = 0.10, p < .001$). Thus, the quadratic growth model would provide evidence for a lower growth rate for high achievers and a higher, albeit decelerating, growth rate for the other students and thus for a pattern of compensation.

In order to inspect the timing of differential academic development, the piecewise growth

curve was estimated. The first slope was smaller for high-achieving children ($\Delta_{lin1} = -0.53, p < .001$). However, the second slope was not affected by group membership ($\Delta_{lin2} = 0.00, p = .99$). These results suggest that between Grades 5 and 6, compensation was taking place. This compensation was substantial, decreasing the initial achievement gap between both groups by about 42 percent. Afterwards, both groups developed at the same pace.

3.3.2. Mathematics Achievement

Results from multigroup models for mathematics (Table 8) resembled the results for reading. Group membership was related to the shape of the quadratic growth curve such that the difference between the linear growth factors of the two groups was $-0.59 (p < .001)$, and the difference in quadratic growth was $0.14 (p < .001)$. Thus, high achievers showed a slower growth process but did not show negative acceleration, while the other students exhibited a steeper growth which slowed down over time (Figure 2). The piecewise Model 4 showed that the first slope in mathematics skill development was lower for high achievers ($\Delta_{lin1} = -0.49, p < .001$), decreasing the original achievement gap by about 31 percent, but the groups did not differ in the second slope ($\Delta_{lin2} = -0.09, p = .16$). The differences between the two groups were also confirmed by an alternative model in which we estimated direct paths from a dummy group membership factor to the growth factors rather than using a multigroup approach (details can be found in Supplement C).

3.4. Robustness checks

To determine in how far results are a product of choices made during data analysis, we conducted a series of further analyses in which we systematically changed factors that may have influenced the results, namely the methods used when scaling the data, the method for dealing with missing data, and the cut-off criterion used for defining high achievers. We thereby

followed the idea of a multiverse analysis proposed by Steegen, Tuerlinckx, Gelman and Vanpaemel (2016) as well as the specification curve approach of Simonsohn, Simmons and Nelson (2015). Our results proved to be robust, with all effects pointing in the same direction. More specifically, the standardized slope differences between both groups had a mean of $\bar{d}_{lin1} = 1.22$ across all analysis models in reading and a mean of $\bar{d}_{lin1} = 0.86$ across all models in mathematics. The details of these analyses and results are in Supplement B.

4. Discussion

In this study, our goal was to examine the differential academic development of high-achieving students in secondary school in both reading and mathematics. Based on previous research, competitive hypotheses were formulated predicting (H1.a) that high achievers would extend their lead with respect to their achievement (cumulative advantage; Matthew effect), (H1.b) that previously lower achieving classmates would catch up over time (compensation), or (H1.c) that the two groups would develop at the same pace and in parallel.

Overall, our results did not support the Matthew effect hypothesis in high-track secondary schools in either reading or mathematics (H1a. rejected). Our results rather supported the compensation hypothesis for both reading and mathematics because initially high-achieving students showed less growth than other students (H1.b sustained). The results are aligned with earlier work that found Matthew effects in elementary education but not for an extended period of time after the children started school (Baumert et al., 2012). The effect sizes we found in our sample were quite high compared with other studies. A reason for this might be the relative homogeneity of our sample

The absence of Matthew effect patterns in our study could have a variety of causes. On the one hand, high-achieving students might not have been challenged enough and might not

have found sufficient opportunities to develop their skills in school. Although high-track secondary schools are supposed to serve the highest achieving students in the educational system, teachers do not seem to succeed in enabling these students to progress more rapidly. Different studies have shown that on average, teachers differentiate very little and do not seem to orientate their teaching toward the most able students but rather to an imaginary average student (Archambault et al., 1993; Jennek et al., 2018). The supposition that high-track secondary schools do not optimally support high achievers has been supported by research showing similar patterns of academic development in high achievers who make an early transition into Gymnasium compared with comparable students who stay in primary school for 2 more years, a choice that is possible in certain German states (Baumert et al., 2009). On the other hand, for those high-track students with relatively lower achievement, the positive effects of transitioning to the high-track schools seem to have outweighed the negative effects of a lower achievement rank so that they were not at a disadvantage as might be expected.

It is possible that teachers have played an active part in aiming for achievement homogeneity in their classes: Depending on their conception of justness, teachers allocate opportunities to individual students according to the principles of need, justness, or equality (Schwippert & Walker, 2003). If teachers are motivated by the need principle, they should allocate more attention and resources to students with lower achievement to help ensure that they do not fall further behind. Accordingly, Nurmi, Viljaranta, Tolvanen, & Aunola (2012) as well as Kiuru et al. (2015) have shown for primary teachers that they directed more active instruction to lower performing students than to high performers. For specific tracks in secondary school, such research is missing. However, it is not only that the individual teachers in class might have distributed their efforts unevenly. It might also be the case that some students with lower

achievement in high-track schools received additional remediation or out-of-school tutoring, which helped them keep up or even improve substantially. For German primary schools, it has been shown that schools are more likely to provide remedial tutoring for students with difficulties than they are to provide extracurricular enrichment opportunities for high-achieving students (Neuendorf, Kuhl, & Jansen, 2017). Future research is needed to investigate whether variations in the use of differentiated and adaptive instruction or enrichment opportunities in school make a difference in the achievement trajectories of high-achieving students. Also, further research could investigate whether the abovementioned speculations hold and teachers are deliberately or unwittingly less likely to promote high achievers than other students, especially in the early grades of secondary school.

The results in reading and mathematics are in agreement concerning the lack of Matthew effects within the highest secondary school track (H3 rejected). This could either mean that the same processes are at play in both domains, but the compensation effects could also be stemming from different causes leading to the same result in both subjects. Reading practice, for example, is less confined to the school context: Secondary school students need reading competencies in their everyday life. Consequently, the additional time students read outside of school or in other school subjects might help them catch up more quickly. In mathematics, students having problems with the lesson content might be more easily identified as tasks usually have a well-defined solution and mistakes can be easily detected. Subsequently, teachers can give special attention to these students. Both reading and mathematics skills might have in common that students differ in their onset of development and developmental trajectories similarly follow a pattern of slowing growth across the school career (Bloom, Hill, Black, & Lipsey, 2008), resulting in catching-up effects.

Our analyses confirmed that growth trajectories as well as differences therein followed a non-linear shape (H2 sustained). Differences in growth between the two achievement groups seemed to occur mainly in the first period of measurement, that is, from Grade 5 to Grade 6. On the one hand, it is plausible that, especially in the first year after the transition, students adjust to the new demands placed on them, and teachers have sufficiently homogenized the students' achievement levels so that further learning can proceed at a more even pace for all. On the other hand, compensation between the first two measurement occasions is a pattern that we would expect given the effect of regression to the mean. Those scoring highest on a first test will, for statistical reasons, score lower on average when measured a second time. Therefore, the compensation effects we found could also be statistical artefacts. This is a fundamental problem when analyzing the development of extreme groups over time (Campbell & Kenny, 2003). One possibility suggested in the literature is the usage of residualized change scores as a supplement to regular growth analysis. Thus, in an additional analysis, which is included in Supplement D, we calculated residualized change scores, but we cannot rule out that results are partly caused by regression to the mean.

4.1. Limitations

Our study has some limitations. First, there was a great deal of attrition between Grades 7 and 8. This dropout was mainly due to the requirement of a new informed consent form after Grade 7 (Homuth et al., 2017). We used the FIML procedure, which actually requires missing values to occur “at random” to deal with the missing data (Enders, 2010; see Section 2.4). However, Homuth et al. (2017) showed that dropout was selective in that, among other reasons, students with less educated parents and a lower ISEI score were more likely to terminate their attendance. Enders (2011) recommended that a sensitivity analysis be performed by estimating a

similar model using multiple competing missing data treatment methods. In a multiverse follow-up analysis, we therefore additionally fit the selection model to the data (Enders, 2011). This led to essentially the same results, which we have included in Supplement B.

Further, the model fit in reading was not satisfactory (see Table 5). As the inspection of the observed curves showed, the curve did not closely follow a linear or quadratic shape. We accepted imposing a less-than-optimal model to the data in the interest of answering our substantive question, especially in comparing the model results between reading and mathematics. However, with more points of measurement per year, it might be easier to describe the shape of the curve in reading because more measurement occasions allow for greater flexibility in model building.

When conducting research on extreme groups, the interpretation of results rests on the ability of the instrument to properly differentiate between students at the ends of the distribution. Regrettably, the test instruments used in the BiKS-study differentiate better at the lower ends of the distribution. Particularly the reading test suffers from ceiling effects at T2 and T3. Of course, this is concerning, as the effect of compensation could be caused by those high achievers not being able to demonstrate their competencies fully. Future research should strive to develop and apply tests which are able to properly assess achievement at all levels. Adaptive testing would be a possibility to increase test information and reduce measurement error without having the problem of too long tests or motivational problems in students for whom the test is too difficult.

Another limitation of our study is the small number of linking items. According to Angoff (1984), as a rule of thumb, no less than 20 items should be used. Whereas a larger number of linking items might reduce the standard error of linking, there are different views on the criteria for including or excluding linking items (Robitzsch, Dörfler, Pfoest, & Artelt, 2011;

Taherbhai & Seo, 2013). We checked whether different recommended strategies (using all common items as linking items; discarding items showing DIF from the linking pool but leaving them in the tests; discarding items showing DIF from the tests altogether) would change the results (see Supplement B). We found an effect on the magnitude of effects in reading, but not on their direction. Moreover, the rank-order stability in freely estimated anchor items was between .80 and .96 in reading and between .94 and .97 in mathematics. We therefore concluded that the anchor items were sufficiently consistent across waves. However, future research could substantiate the findings if longer tests could be used.

A point that could be criticized in our study is the use of a cut-off criterion to categorize students into the group of high achievers. For one thing, achievement is obviously a continuum, and whether there is a threshold at which a qualitative difference in learning and development processes between those above and below an arbitrary cut-off can be observed seems disputable. We paid attention to this fact by estimating Models 1 and 2 for the total sample. Here, the nonsignificant correlation between the intercept and slope would imply that parallel development had taken place. Models 3 and 4, in which students were grouped according to our cut-off criterion, indicated compensatory development. These different results seem to legitimize the use of categories for analytical purposes when inferences should be drawn about high achievers. However, the question of whether it is possible to find subgroups of students that follow distinct developmental patterns and whether these subgroups are related to different initial achievement levels should be the subject of future research, for example, by using latent class growth analyses (Jung & Wickrama, 2008).

4.2. Conclusion

Because students come to school with different skills, it is a challenge for teachers to

meet the needs of children who differ substantially in prior achievement. The transition to secondary school in Germany signifies a major change in the educational context—in peers, in teachers, and in teaching practices—that could have a differential impact on patterns of development. It was our aim to clarify whether high-achieving students show different curves for reading and/or mathematics development than other students, whether these other students catch up during secondary school, or whether the two groups show similar rates of growth. Our results favor the compensation hypothesis for both domains. Thus, we found no support for the notion of Matthew effects in high-track secondary school in reading or in mathematics.

In how far these results can be generalized remains an open question. While some explanatory approaches to the results are universal in nature (for example the lagged non-linear skill development), others might be confined to this specific context of Germany and to these specific competencies under study (for example the employment of certain teaching strategies and the perceived role of a teacher). Thus, replicating our findings within other contexts could help in determining the extent to which these findings are generalizable.

Whereas the teachers of this sample of students seem to be successful in fostering academic progress in all students similarly, it might be expected that students with high initial competencies can learn at a faster rate when challenged adequately. Therefore, the promotion of high achievers in lower secondary school might profit from research on the effectiveness of applying differentiating strategies in secondary school.

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References

- Aarnoutse, C., & van Leeuwe, J. (2000). Development of poor and better readers during the elementary school. *Educational Research and Evaluation*, 6(3), 251–278.
[https://doi.org/10.1076/1380-3611\(200009\)6:3;1-A;FT251](https://doi.org/10.1076/1380-3611(200009)6:3;1-A;FT251)
- Aarnoutse, C., van Leeuwe, J., Voeten, M., & Oud, H. (2001). Development of decoding, reading comprehension, vocabulary and spelling during the elementary school years. *Reading and Writing: An Interdisciplinary Journal*, 14, 61–89.
- Archambault, F. X., Westberg, K. L., Brown, S. W., Hallmark, B. W., Zhang, W., & Emmons, C. L. (1993). Classroom practices used with gifted third and fourth grade students. *Journal for the Education of the Gifted*, 16(2), 103–119. <https://doi.org/10.1177/016235329301600203>
- [dataset] Artelt, C., Blossfeld, H.-P., Faust, G., Roßbach, H.-G., & Weinert, S. (2013). *Bildungsprozesse, Kompetenzentwicklung und Selektionsentscheidungen im Vorschul- und Schulalter (BiKS-8- 14)* [Educational processes, competence development and selection decisions in preschool and school age]. Institut zur Qualitätsentwicklung im Bildungswesen. Datset, https://doi.org/10.5159/IQB_BIKS_8_14_v2.
- Bannister, N. A. (2016). Breaking the spell of differentiated instruction through equity pedagogy and teacher community. *Cultural Studies of Science Education*, 11(2), 335–347.
<https://doi.org/10.1007/s11422-016-9766-0>
- Bast, J., & Reitsma, P. (1997). Mathew effects in reading: A comparison of latent growth curve models and simplex models with structured means. *Multivariate Behavioral Research*, 32(2), 135–167. https://doi.org/10.1207/s15327906mbr3202_3
- Baumert, J., Becker, M., Neumann, M., & Nikolova, R. (2009). Frühübergang in ein grundständiges Gymnasium – Übergang in ein privilegiertes Entwicklungsmilieu? [Early

transition into the academic track of secondary schooling – Transfer into a privileged learning environment?]. *Zeitschrift Für Erziehungswissenschaft*, 12(2), 189–215.

<https://doi.org/10.1007/s11618-009-0072-4>

Baumert, J., Lehmann, R., Lehrke, M., Clausen, M., Hosenfeld, I., Neubrand, J., . . . Günther, W. (1998). *Testaufgaben Mathematik TIMSS 7./8. Klasse (Population 2)*. Berlin: Max-Planck-Institut für Bildungsforschung.

Baumert, J., Maaz, K., Stanat, P., Watermann, R. (2009). Schulkomposition oder Institution – was zählt? Schulstrukturen und die Entstehung schulformspezifischer Entwicklungsverläufe [Compositional or institutional factors—What counts at school? School structures and the Emergence of track-specific developmental trajectories]. *Die Deutsche Schule*, 101(1), 33-46.

Baumert, J., Nagy, G., & Lehmann, R. (2012). Cumulative advantages and the emergence of social and ethnic inequality: Matthew effects in reading and mathematics development within elementary schools? *Child Development*, 83(4), 1347–1367. <https://doi.org/10.1111/j.1467-8624.2012.01779.x>

Baumert, J., Stanat, P., & Watermann, R. (2006). Schulstruktur und die Entstehung differenzieller Lern- und Entwicklungsmilieus [School structure and the emergence of a differential learning and development environment]. In J. Baumert, P. Stanat, & R. Watermann (Eds.), *Herkunftsbedingte Disparitäten im Bildungswesen: Differenzielle Bildungsprozesse und Probleme der Verteilungsgerechtigkeit: Vertiefende Analysen im Rahmen von PISA 2000* (pp. 95–188). Wiesbaden: VS Verlag für Sozialwissenschaften. https://doi.org/10.1007/978-3-531-90082-7_4

Becker, M., Neumann, M., Tetzner, J., Böse, S., Knoppick, H., Maaz, K., . . . Lehmann, R. (2014). Is early ability grouping good for high-achieving students' psychosocial

- development? Effects of the transition into academically selective schools. *Journal of Educational Psychology*, 106(2), 555–568. <https://doi.org/10.1037/a0035425>
- Bloom, H. S., Hill, C. J., Black, A. R., & Lipsey, M. W. (2008). *Performance trajectories and performance gaps as achievement effect-size benchmarks for educational interventions* (MDRC Working Papers on Research Methodology). Retrieved from MDRC website: https://www.mdrc.org/sites/default/files/full_473.pdf
- Brighton, C. M., Hertberg, H. L., Moon, T. R., Tomlinson, C. A., & Callahan, C. M. (2005). *The feasibility of high-end learning in a diverse middle school* (RM05210). Storrs, Connecticut: National Research Center on the Gifted and Talented.
- Campbell, D. T., & Kenny, D. A. (2003). *A primer on regression artifacts: Donald T. Campbell, David A. Kenny* (Reprinted.). *Methodology in the social sciences*. New York: Guilford Press.
- Caro, D. H., Lenkeit, J., & Kyriakides, L. (2016). Teaching strategies and differential effectiveness across learning contexts: Evidence from PISA 2012. *Studies in Educational Evaluation*, 49, 30–41. <https://doi.org/10.1016/j.stueduc.2016.03.005>
- Ceci, S. J., & Papierno, P. B. (2005). The rhetoric and reality of gap closing: When the "have-nots" gain but the "haves" gain even more. *The American Psychologist*, 60(2), 149–160. <https://doi.org/10.1037/0003-066X.60.2.149>
- Chou, C.-P., Yang, D., Pentz, M. A., & Hser, Y.-I. (2004). Piecewise growth curve modeling approach for longitudinal prevention study. *Computational Statistics & Data Analysis*, 46(2), 213–225. [https://doi.org/10.1016/S0167-9473\(03\)00149-X](https://doi.org/10.1016/S0167-9473(03)00149-X)
- Claessens, A., & Engel, M. (2013). How important is where you start? Early mathematics knowledge and later school success. *Teachers College Record*, 115(6), 1–29.
- Cunningham, Anne E.; Stanovich, Keith E. (1997). Early reading acquisition and its relation to

- reading experience and ability 10 years later. *Developmental Psychology*, 33(6), 934–945.
<https://doi.org/10.1037/0012-1649.33.6.934>
- Dar, Y., & Resh, N. (1986). Classroom intellectual composition and academic achievement. *American Educational Research Journal*, 23(3), 357–374.
<https://doi.org/10.3102/00028312023003357>
- Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series B*, 39(1), 1–38.
- DFG-Forschergruppe „Bildungsprozesse, Kompetenzentwicklung und Selektionsentscheidungen im Vorschul- und Schulalter“ (BiKS). (n.d.). *Codebuch zur Kompetenzerhebung Welle 4: BiKS-8-14 Sekundarstufe* [Codebook for Competence Assessment Wave 4: BiKS-8-14 Secondary School]. Retrieved from https://www.iqb.hu-berlin.de/fdz/studies/BiKS_8-14/Kompetenzerhebung_3.pdf
- DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology*, 32(1), 271–297. <https://doi.org/10.1146/annurev.soc.32.061604.123127>
- Dockx, J., Fraine, B. de, & Vandecandelaere, M. (2018). Does the track matter? A comparison of students' achievement in different tracks. *Journal of Educational Psychology*. Advance online publication. <https://doi.org/10.1037/edu0000305>
- Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., . . . Japel, C. (2007). School readiness and later achievement. *Developmental Psychology*, 43(6), 1428–1446. <https://doi.org/10.1037/0012-1649.43.6.1428>
- Embretson, S. E., & Reise, S. (2000). *Item response theory for psychologists. Multivariate applications*. Mahwah, N.J.: Lawrence Erlbaum Associates, Publishers.

- Enders, C. K. (2010). *Applied missing data analysis. Methodology in the social sciences*. New York: Guilford Press.
- Enders, C. K. (2011). Missing not at random models for latent growth curve analyses. *Psychological Methods*, 16(1), 1–16. <https://doi.org/10.1037/a0022640>
- Fischer, G. H. (1995). Linear logistic models for change. In G. H. Fischer & I. W. Molenaar (Eds.), *Rasch models. Foundations, recent developments, and applications* (pp. 157–180). New York: Springer.
- Francis, D. J., Shaywitz, S. E., Stuebing, K. K., Shaywitz, B. A., & Fletcher, J. M. (1996). Developmental lag versus deficit models of reading disability: A longitudinal, individual growth curves analysis. *Journal of Educational Psychology*, 88(1), 3–17. <https://doi.org/10.1037/0022-0663.88.1.3>
- Fyfe, E. R., Rittle-Johnson, B., & DeCaro, M. S. (2012). The effects of feedback during exploratory mathematics problem solving: Prior knowledge matters. *Journal of Educational Psychology*, 104(4), 1094–1108. <https://doi.org/10.1037/a0028389>
- Gagné, F. (2009). Building gifts into talents: Detailed overview of the DMGT 2.0. In B. MacFarlane & T. Stambaugh (Eds.), *Leading change in gifted education: The festschrift of Dr. Joyce VanTassel-Baska* (pp. 61–80). Waco, TX: Prufrock Press.
- Ganzeboom, H. B., Graaf, P. M. de, & Treiman, D. J. (1992). A standard international socio-economic index of occupational status. *Social Science Research*, 21(1), 1–56. [https://doi.org/10.1016/0049-089X\(92\)90017-B](https://doi.org/10.1016/0049-089X(92)90017-B)
- Götz, L., Lingel, K., & Schneider, W. (2013). *DEMAT 6+: Deutscher Mathematiktest für sechste Klassen* [German Mathematics Test for Sixth Classes]: Hogrefe.
- Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. San Diego, CA:

Academic Press.

Heimendinger, J., & Laird, N. (1983). Growth changes: Measuring the effect of an intervention.

Evaluation Review, 7(1), 80–95. <https://doi.org/10.1177/0193841X8300700105>

Homuth, C., Schmitt, M., Lorenz, C., & Mann, D. (2017). Warum ein erneutes

Genehmigungsverfahren im laufenden Längsschnitt weitreichende Folgen für die

Datenqualität hat [Why does a new consent procedure during an ongoing longitudinal study

influence data quality]. *Journal for Educational Research Online*, 9(1), 7–31. Retrieved from

<http://www.j-e-r-o.com/index.php/jero/article/viewFile/731/302>

Jennek, J., Gronostaj, A., & Vock, M. (2018). Wie Lehrkräfte im Englischunterricht

differenzieren. Eine Re-Analyse der DESI-Videos [Differentiation among German teachers of

English: Reanalyzing the DESI Study videos]. *Unterrichtswissenschaft*. Advance online

publication. <https://doi.org/10.1007/s42010-018-0027-7>

Jordan, N. C., Hanich, L. B., & Kaplan, D. (2003). A longitudinal study of mathematical

competencies in children with specific mathematics difficulties versus children with comorbid

mathematics and reading difficulties. *Child Development*, 74(3), 834–850.

<https://doi.org/10.1111/1467-8624.00571>

Jung, T., & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and

growth mixture modeling. *Social and Personality Psychology Compass*, 2(1), 302–317.

<https://doi.org/10.1111/j.1751-9004.2007.00054.x>

Kim, S. (2006). A comparative study of IRT fixed parameter calibration methods. *Journal of*

Educational Measurement, 43(4), 355–381. <https://doi.org/10.1111/j.1745-3984.2006.00021.x>

Kiss, D. (2013). The impact of peer achievement and peer heterogeneity on own achievement

growth: Evidence from school transitions. *Economics of Education Review*, 37, 58–65.

<https://doi.org/10.1016/j.econedurev.2013.08.002>

- Kiuru, N., Nurmi, J.-E., Leskinen, E., Torppa, M., Poikkeus, A.-M., Lerkkanen, M.-K., & Niemi, P. (2015). Elementary school teachers adapt their instructional support according to students' academic skills: A variable and person-oriented approach. *International Journal of Behavioral Development*, 39(5), 391–401. <https://doi.org/10.1177/0165025415575764>
- Kolen, M. J., & Brennan, R. L. (2014). *Test equating, scaling, and linking*. New York, NY: Springer New York.
- Kühn, P., Sachse, S., & Suchodoletz, W. von. (2015). Sprachentwicklungsverzögerung: Was wird aus Late Bloomern? [Language delay: What is the prognosis of late bloomers?]. *Klinische Padiatrie*, 227(4), 213–218. <https://doi.org/10.1055/s-0035-1547310>
- Kulik, C.-L. C., & Kulik, J. A. (1982). Effects of Ability Grouping on Secondary School Students: A Meta-analysis of Evaluation Findings. *American Educational Research Journal*, 19(3), 415–428. <https://doi.org/10.3102/00028312019003415>
- Kunter, M., Brunner, M., Baumert, J., Klusmann, U., Krauss, S., Blum, W., . . . Neubrand, M. (2005). Der Mathematikunterricht der PISA-Schülerinnen und -Schüler [Quality of mathematics instruction across school types: Findings from PISA 2003]. *Zeitschrift Für Erziehungswissenschaft*, 8(4), 502–520. <https://doi.org/10.1007/s11618-005-0156-8>
- Li, A. K. F., & Adamson, G. (1992). Gifted Secondary Students' Preferred Learning Style: Cooperative, Competitive, or Individualistic? *Journal for the Education of the Gifted*, 16(1), 46–54. <https://doi.org/10.1177/016235329201600106>
- Linchevski, L., & Kutscher, B. (1998). Tell me with whom you're learning, and I'll tell you how much you've learned: Mixed-ability versus same-ability grouping in mathematics. *Journal for Research in Mathematics Education*, 533–554. <https://doi.org/10.2307/749732>

- Lorenz, C., Schmitt, M., Lehl, S., Mudiappa, M., & Rossbach, H.-G. (2013). The Bamberg BiKS research group. In M. Pfohl, C. Artelt, & S. Weinert (Eds.), *Schriften aus der Fakultät Humanwissenschaften der Otto-Friedrich-Universität Bamberg - 14. The Development of Reading Literacy from Early Childhood to Adolescence. Empirical Findings from the Bamberg BiKS Longitudinal Studies* (pp. 15–34). Bamberg: University of Bamberg Press.
- Lu, Y. (2016). Modeling Math Growth Trajectory—An Application of Conventional Growth Curve Model and Growth Mixture Model to ECLS K-5 Data. *Journal of Educational Issues*, 2(1), 166. <https://doi.org/10.5296/jei.v2i1.9197>
- Ma, X. (2005). A longitudinal assessment of early acceleration of students in mathematics on growth in mathematics achievement☆. *Developmental Review*, 25(1), 104–131. <https://doi.org/10.1016/j.dr.2004.08.010>
- Maaz, K., Trautwein, U., Lüdtke, O., & Baumert, J. (2008). Educational transitions and differential learning environments: How explicit between-school tracking contributes to social inequality in educational outcomes. *Child Development Perspectives*, 2(2), 99–106. <https://doi.org/10.1111/j.1750-8606.2008.00048.x>
- Magrini, A. (2016). dlsem: Distributed-Lag Structural Equation Modelling. Retrieved from <https://CRAN.R-project.org/package=dlsem>
- Marx, H., & Opitz-Karig, U. (2005). *DEMAT5+: Deutscher Mathematiktest für fünfte Klassen* [German Mathematics Test for Fifth Classes]. Leipzig, Germany.
- McCoach, D. Betsy; Siegle, Del (2007): What Predicts Teachers' Attitudes Toward the Gifted? In: *Gifted Child Quarterly* 51(3), S. 246–254. DOI: 10.1177/0016986207302719.
- Morgan, P. L., Farkas, G., & Wu, Q. (2011). Kindergarten children's growth trajectories in reading and mathematics: Who falls increasingly behind? *Journal of Learning Disabilities*,

44(5), 472–488. <https://doi.org/10.1177/0022219411414010>

- Morgan, P. L., & Fuchs, D. (2007). Is there a bidirectional relationship between children's reading skills and reading motivation? *Exceptional Children*, 73(2), 165–183.
- Muthén, L. K., & Muthén, B. O. (1998-2011). Mplus User's Guide. Sixth Edition. Los Angeles, CA: Muthén & Muthén.
- Nelson, G., & Powell, S. R. (2018). A systematic review of longitudinal studies of mathematics difficulty. *Journal of learning disabilities*, 51(6), 523–539.
- Neuendorf, C., Kuhl, P., & Jansen, M. (2017). Leistungsstarke Schülerinnen und Schüler in Deutschland [High-achieving students in Germany]. In P. Stanat, S. Schipolowski, C. Rjosk, S. Weirich, & N. Haag (Eds.), *IQB-Bildungstrend 2016: Kompetenzen in den Fächern Deutsch und Mathematik am Ende der 4. Jahrgangsstufe im zweiten Ländervergleich* (pp. 317–334). Münster: Waxmann.
- Nurmi, J.-E., Viljaranta, J., Tolvanen, A., & Aunola, K. (2012). Teachers adapt their instruction according to students' academic performance. *Educational Psychology*, 32(5), 571–588. <https://doi.org/10.1080/01443410.2012.675645>
- OECD. (2016). *PISA 2015 results (Volume I): Excellence and equity in education*. PISA. Paris: OECD Publishing.
- Pekrun, R., Götz, T., Jullien, S., Zirngibl, A., vom Hofe, R., & Blum, W. (2003). *Skalenhandbuch PALMA: 2. Messzeitpunkt (6. Klassenstufe)*. München.
- Pfost, M., Hattie, J., Dörfler, T., & Artelt, C. (2014). Individual differences in reading development: A review of 25 years of empirical research on Matthew effects in reading. *Review of Educational Research*, 84(2), 203–244. <https://doi.org/10.3102/0034654313509492>
- Pfost, M., & Artelt, C. (2013). Reading literacy development in secondary school and the effect

- of differential institutional learning environments. In M. Pfof, C. Artelt, & S. Weinert (Eds.), *Schriften aus der Fakultät Humanwissenschaften der Otto-Friedrich-Universität Bamberg - 14. The Development of Reading Literacy from Early Childhood to Adolescence. Empirical Findings from the Bamberg BiKS Longitudinal Studies* (pp. 229–277). Bamberg: University of Bamberg Press.
- Pfof, M., Dörfler, T., & Artelt, C. (2010). Der Zusammenhang zwischen außerschulischem Lesen und Lesekompetenz [The relation between extra-curricular reading behavior and reading competence: Results from a longitudinal study at the transition from primary to secondary school]. *Zeitschrift Für Entwicklungspsychologie Und Pädagogische Psychologie*, 42(3), 167–176. <https://doi.org/10.1026/0049-8637/a000017>
- Pfof, M., Dörfler, T., & Artelt, C. (2012). Reading competence development of poor readers in a German elementary school sample: an empirical examination of the Matthew effect model. *Journal of Research in Reading*, 35(4), 411–426. <https://doi.org/10.1111/j.1467-9817.2010.01478.x>
- Pfof, M., Dörfler, T., & Artelt, C. (2013). Students' extracurricular reading behavior and the development of vocabulary and reading comprehension. *Learning and Individual Differences*, 26, 89–102. <https://doi.org/10.1016/j.lindif.2013.04.008>
- Pfof, M., Karing, C., Lorenz, C., & Artelt, C. (2010). Schereneffekte im ein- und mehrgliedrigen Schulsystem [Fan spread effects in a tracked and a nontracked school system]. *Zeitschrift Für Pädagogische Psychologie*, 24(3-4), 259–272. <https://doi.org/10.1024/1010-0652/a000025>
- Phillips, N., & Lindsay, G. (2006). Motivation in gifted students. *High Ability Studies*, 17(1), 57–73. <https://doi.org/10.1080/13598130600947119>

- Plucker, J. A., & Callahan, C. M. (2014). Research on giftedness and gifted education: Status of the field and considerations for the future. *Exceptional Children*, 80(4), 390–406.
<https://doi.org/10.1177/0014402914527244>
- Protopapas, A., Parrila, R., & Simos, P. G. (2016). In Search of Matthew Effects in Reading. *Journal of Learning Disabilities*, 49(5), 499–514. <https://doi.org/10.1177/0022219414559974>
- R Core Team. (2018). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>
- Rambo-Hernandez, K. E., & McCoach, D. B. (2014). High-Achieving and Average Students' Reading Growth: Contrasting School and Summer Trajectories. *The Journal of Educational Research*, 108(2), 112–129. <https://doi.org/10.1080/00220671.2013.850398>
- Robitzsch, A., Dörfler, T., Pfof, M., & Artelt, C. (2011). Die Bedeutung der Itemauswahl und der Modellwahl für die längsschnittliche Erfassung von Kompetenzen [Relevance of item selection and model selection for assessing the development of competencies: The development in reading competence in primary school students]. *Zeitschrift Für Entwicklungspsychologie Und Pädagogische Psychologie*, 43(4), 213–227.
<https://doi.org/10.1026/0049-8637/a000052>
- Scammacca, N., Fall, A.-M., Capin, P., Roberts, G., & Swanson, E. (2019). Examining factors affecting reading and math growth and achievement gaps in grades 1–5: A cohort-sequential longitudinal approach. *Journal of Educational Psychology*. Advance online publication. <https://doi.org/10.1037/edu0000400>
- Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research*, 99(6), 323–338. <https://doi.org/10.3200/JOER.99.6.323-338>

- Schwippert, K., & Walker, M. (2003). Homogenous and high performing classes: The case of optimal classes. *Studies in Educational Evaluation*, 29(2), 109–128.
[https://doi.org/10.1016/S0191-491X\(03\)00018-X](https://doi.org/10.1016/S0191-491X(03)00018-X)
- Shaywitz, B. A., Holford, T. R., Holahan, J. M., Fletcher, J. M., Stuebing, K. K., Francis, D. J., & Shaywitz, S. E. (1995). A matthew effect for IQ but not for reading: Results from a longitudinal study. *Reading Research Quarterly*, 30(4), 894–906.
- Shin, T., Davison, M. L., Long, J. D., Chan, C.-K., & Heistad, D. (2013). Exploring gains in reading and mathematics achievement among regular and exceptional students using growth curve modeling. *Learning and Individual Differences*, 23, 92–100.
<https://doi.org/10.1016/j.lindif.2012.10.002>
- Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2015). Specification Curve: Descriptive and Inferential Statistics on All Reasonable Specifications. *SSRN Electronic Journal*. Advance online publication. <https://doi.org/10.2139/ssrn.2694998>
- Skibbe, L. E., Grimm, K. J., Stanton-Chapman, T. L., Justice, L. M., Pence, K. L., & Bowles, R. P. (2008). Reading trajectories of children with language difficulties from preschool through fifth grade. *Language, Speech, and Hearing Services in Schools*, 39, 475–486.
- Slavin, R. E. (1990). Achievement effects of ability grouping in secondary schools: A best-evidence synthesis. *Review of Educational Research*, 60(3), 471–499.
<https://doi.org/10.2307/1170761>
- Snow, R. E., & Lohman, D. F. (1984). Toward a theory of cognitive aptitude for learning from instruction. *Journal of Educational Psychology*, 76(3), 347–376.
<https://doi.org/10.1037/0022-0663.76.3.347>
- Stanovich, K. E. (1986). Matthew effects in reading: Some consequences of individual

differences in the acquisition of literacy. *Reading Research Quarterly*, XXI(4), 360–406.

Steege, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing Transparency Through a Multiverse Analysis. *Perspectives on Psychological Science : a Journal of the Association for Psychological Science*, 11(5), 702–712.

<https://doi.org/10.1177/1745691616658637>

Taherbhai, H., & Seo, D. (2013). The philosophical aspects of IRT equating: Modeling drift to evaluate cohort growth in large scale assessments. *Educational Measurement: Issues and Practice*, 32(1), 2–14.

Tomlinson, C. A., Brighton, C., Hertberg, H., Callahan, C. M., Moon, T. R., BrimiJoin, K., . . . Reynolds, T. (2003). Differentiating Instruction in Response to Student Readiness, Interest, and Learning Profile in Academically Diverse Classrooms: A Review of Literature. *Journal for the Education of the Gifted*, 27(2-3), 119–145.

<https://doi.org/10.1177/016235320302700203>

Trautwein, U., Lüdtke, O., Marsh, H. W., & Nagy, G. (2009). Within-school social comparison: how students perceive the standing of their class predicts academic self-concept. *Journal of Educational Psychology*, 101(4), 853–866. <https://doi.org/10.1037/a0016306>

Udvari, S. J., & Schneider, B. H. (2000). Competition and the adjustment of gifted children: A matter of motivation. *Roeper Review*, 22(4), 212–216.

<https://doi.org/10.1080/02783190009554040>

Von Davier, M., & von Davier, A. A. (2004). *A unified approach to IRT scale linking and scale transformation*. Princeton, New Jersey: ETS.

Walberg, H. J., & Tsai, S.-L. (1983). Matthew effects in education. *American Educational Research Journal*, 20(3), 359–373.

Warm, T. A. (1989). Weighted likelihood estimation of ability in item response theory.

Psychometrika, 54, 427–450.

Weirich, S., & Hecht, M. (2018). eatModel. Retrieved from <https://R-Forge.R-project.org/projects/eat/>

Wothke, W. (2000). Longitudinal and multigroup modeling with missing data. In T. D. Little, K. U. Schnabel, & J. Baumert (Eds.), *Modeling longitudinal and multilevel data: Practical issues, applied approaches, and specific examples* (pp. 219-240, 269-281). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Wu, M. L., Adams, R. J., Wilson, & Haldane, S. A. (2007). ACER conquest version 2.0: Camberwell, Victoria, Australia: ACER Press, Australian Council for Educational Research.

Zieky, M. (1993). Practical questions in the use of DIF statistics in test development. In P. W. Holland & H. Wainer (Eds.), *Differential item functioning* (pp. 337–347). Hillsdale, NJ, US: Lawrence Erlbaum Associates, Inc.

Zuckerman, H. (2011). The Matthew Effect Writ Large and Larger: A Study in Sociological Semantics. In Y. Elkana, A. Szigeti, & G. Lissauer (Eds.), *Robert K. Merton and the Future of Sociology. Concepts and the Social Order* (1st ed., pp. 121–164). Central European University Press.

Table 1

Descriptive Statistics

	T1 (Grade 5)	T2 (Grade 6)	T3 (Grade 7)	T4 (Grade 8)	T5 (Grade 9)
<i>N</i> (reading)	1010	855	797	369	334
<i>N</i> (math)	1010	858	761	361	-
<i>M</i> _{reading} (<i>SD</i>)	0.00 (0.64)	0.71 (0.86)	1.00 (1.10)	1.68 (0.91)	1.9 (0.81)
<i>M</i> _{math} (<i>SD</i>)	-0.01 (0.81)	0.72 (1.00)	1.17 (1.02)	1.59 (1.10)	-
Stability reading					
Cor (t ₁)	-	0.44	0.39	0.36	0.38
Cor (t ₂)		-	0.54	0.44	0.33
Cor (t ₃)			-	0.52	0.46
Cor (t ₄)				-	0.57
Stability mathematics					
Cor (t ₁)	-	0.56	0.52	0.45	
Cor (t ₂)		-	0.60	0.51	
Cor (t ₃)			-	0.53	

Note. Descriptive statistics were based on WLE scores. The data from the first wave of measurement were scaled with the Conquest option constraints = cases, that is, the mean of the latent dimension was set to zero. The following waves of measurement were anchored to the scale of the first measurement occasion.

Table 2

Participant Demographic Information

	Total sample	Reading		Math	
	<i>M (SD)</i>	High achievers <i>M (SD)</i>	Other students <i>M (SD)</i>	High achievers <i>M (SD)</i>	Other students <i>M (SD)</i>
1. <i>N</i>	1010	157	853	159	851
2. Gender (% male)	45.45	46.50	45.25	48.43	44.89
3. Age (years)	10.90 (0.40)	10.89 (0.40)	10.90 (0.40)	10.81 (0.38)	10.92 (0.40) *
4. Parental university entry certificate (%)	68.90	76.16	67.51	78.67	67.05 *
5. Socioeconomic status (HISEI)	58.05 (15.61)	61.63 (15.02)	57.38 (15.64) *	62.08 (14.68)	57.29 (15.67) *
6. Immigration background (%)	18.97	15.13	19.70	12.00	20.28 *
7. Reading at t1	0.00 (0.64)	1.04 (0.41)	-0.19 (0.46) *	0.44 (0.68)	-0.08 (0.60) *
8. Mathematics at t1	-0.01 (0.81)	0.51 (0.82)	-0.11 (0.78) *	1.27 (0.51)	-0.25 (0.61) *

Note. HISEI = highest household international socio-economic index of occupational status (Ganzeboom, Graaf, & Treiman, 1992), students with an immigration background had either one or two parents who were born abroad.

* $p < .01$.

Table 3

Effect Sizes of Between-Group Differences in Growth

	T1-T2	T1-T3	T1-T4	T1-T5
Reading				
<i>d</i>	-1.15	-1.15	-1.40	-1.08
Mathematics				
<i>d</i>	-0.82	-1.00	-1.00	-

Note. Shown are the group differences (high achievers vs. other students) in gain scores between the first and the second (T1-T2), third (T1-T3), fourth (T1-T4) or fifth (T1-T5) measurement point. Effect sizes *d* are calculated using the two group's raw gain score and SD with a pooled SD adjusted for group size differences according to Hedges & Olkin (1985).

Table 4

Results of Latent Growth Curve Models (LGCMs) for Reading Development

	Model 1			Model 2		
	Est	(SE)		Est	(SE)	
Mean structure						
Intercept	0.05	(0.03)		0.01	(0.03)	
Linear slope	0.47	(0.01)	*	0.67	(0.04)	*
Quadratic slope				-0.06	(0.01)	*
Covariances						
Intercept – linear slope	0.01	(0.01)		0.01	(0.01)	
Variance structure						
Intercept	0.24	(0.02)	*	0.24	(0.02)	*
Linear slope	0.02	(0.00)	*	0.02	(0.00)	*
Quadratic slope				0.00	(0.00)	

Note. Model 1 = linear growth curve model; Model 2 = quadratic growth curve model.

* $p < .01$.

Table 5

Fit Statistics for all Models

	CFI	RMSEA	SRMR	AIC	BIC
Reading					
Model 1	0.81	0.12	0.11	7741.95	7791.13
Model 2	0.87	0.11	0.13	7671.51	7725.61
Model 3	0.76	0.14	0.16	7021.11	7129.3
Model 4	0.85	0.11	0.12	6965.99	7084.02
Mathematics					
Model 1	0.93	0.11	0.06	7397.38	7441.64
Model 2	0.99	0.05	0.04	7331.02	7380.2
Model 3	0.96	0.08	0.07	6714.65	6813.01
Model 4	0.82	0.14	0.13	6803.63	6882.31

Note. Model 1 = linear growth curve, Model 2 = quadratic growth curve model, Model 3 = quadratic multigroup model, Model 4 = piecewise multigroup model, CFI = comparative fit index, RMSEA = root mean square error of approximation, SRMR = standardized root mean square residual, AIC = Akaike information criterion, BIC = Bayesian information criterion. The cutoff criteria for model fit are: $CFI \geq .95$, $RMSEA < .08$, $SRMR \leq .08$ (Schreiber, Nora, Stage, Barlow, & King, 2006).

Table 6

Results of Latent Growth Curve Models (LGCMs) for Mathematics Development

	Model 1			Model 2		
	Est	(SE)		Est	(SE)	
Mean structure						
Intercept	0.03	(0.05)		-0.01	(0.05)	
Linear slope	0.54	(0.02)	***	0.82	(0.05)	***
Quadratic slope				-0.12	(0.02)	***
Covariances						
Intercept – linear slope	0.02	(0.02)		0.03	(0.02)	
Variance structure						
Intercept	0.42	(0.05)	***	0.42	(0.05)	***
Linear slope	0.03	(0.01)	*	0.03	(0.01)	**
Quadratic slope				0.00	(0.00)	

Note. Model 1 = linear growth curve model; Model 2 = quadratic growth curve model; the variance in the quadratic slope was fixed to zero for identification purposes.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 7

Results for Nonlinear Multigroup Growth Models in Reading Development: Quadratic Model (Model 3) and Piecewise Model (Model 4)

	Model 3						Model 4					
	High achievers			Other students			High achievers			Other students		
	Est	(SE)		Est	(SE)		Est	(SE)		Est	(SE)	
Mean structure												
Intercept	1.04	-0.03	*	-0.18	-0.02	*	1.04	-0.03	*	-0.19	-0.02	*
Linear slope 1	0.26	-0.09	*	0.76	-0.04	*	0.26	-0.09	*	0.79	-0.04	*
Linear slope 2							0.38 ^a	-0.05	*	0.38 ^a	-0.02	*
Quadratic slope	0.02	-0.03		-0.08	-0.01	*						
Covariances												
Intercept-slope 1	0.00	-0.02		0.01	-0.01							
Intercept-slope 2							-0.01	-0.02		0.01	-0.01	
Variance structure												
Intercept	0.09	-0.03	**	0.13	-0.02	***	0.11	-0.03	***	0.13	-0.02	***

	Model 3				Model 4			
	High achievers		Other students		High achievers		Other students	
	Est	(SE)	Est	(SE)	Est	(SE)	Est	(SE)
Linear slope 1	0.02	(0.01)	0.03	(0) *				
Linear slope 2					0.04	(0.01) *	0.05	(0.01) *

Note. The piecewise model's first slope factor identifies the slope between Time 1 and 2; the second slope factor denotes the linear slope between Time 2 and Time 5. The variance in linear slope 1 in the piecewise model and the variance in the quadratic slope in the quadratic model were fixed to zero for identification purposes. Est = estimated parameter; *SE* = standard error. The means of the latent factors differed significantly between the groups, except for the factors marked with the same superscript.

* $p < .01$.

Table 8

Results for Nonlinear Multigroup Growth Models in Mathematics Development: Quadratic Model (Model 3) and Piecewise Model (Model 4)

	Quadratic model						Piecewise model					
	High achievers			Other students			High achievers			Other students		
	Est	(SE)		Est	(SE)		Est	(SE)		Est	(SE)	
Mean structure												
Intercept	1.26	-0.04	*	-0.25	-0.04	*	1.27	-0.04	*	-0.25	-0.04	*
Linear slope 1	0.32	-0.1	*	0.91	-0.05	*	0.32	-0.08	*	0.82	-0.04	*
Linear slope 2							0.31 ^a	-0.06	*	0.41 ^a	-0.03	*
Quadratic slope	0.00	-0.04		-0.14	-0.02	*						
Covariances												
Intercept – linear slope 1	0.03	-0.03		0.04	-0.02							
Variance structure												
Intercept	0.06	-0.05		0.22	-0.03	*	0.12	-0.04	*	0.28	-0.03	*
Linear slope 1	0.03	-0.02		0.04	-0.01	*						

Note. The piecewise model's first slope factor identifies the slope between Time 1 and 2; the second slope factor denotes the linear slope between Time 2 and Time 5. The variance in linear slope 1 in the piecewise model and the variance in the quadratic slope in the quadratic model were fixed to zero for identification purposes. Est = estimated parameter; *SE* = standard error. The means of the latent factors differed significantly between the groups, except for the factors marked with the same superscript.

* $p < .01$.

Figure 1. Analysis model. (A) Model 1 (linear) and Models 2 and 3 (with additional quadratic growth factor); (B) Model 4 (piecewise growth model with two slopes).

Figure 2. Sample and estimated means for multigroup models. Solid lines are observed scores, dashed lines are scores estimated in a multigroup quadratic latent growth curve model.