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An Integrated Model of Academic Self-Concept Development: Academic Self-Concept, Grades, Test Scores, and Tracking Over 6 Years

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Abstract

Our newly proposed integrated academic self-concept model integrates 3 major theories of academic self-concept formation and developmental perspectives into a unified conceptual and methodological framework. Relations among math self-concept (MSC), school grades, test scores, and school-level contextual effects over 6 years, from the end of primary school through the first 5 years of secondary school (a representative sample of 3,370 German students, 42 secondary schools, 50% male, M age at grade 5 = 11.75) support the

(1) internal/external frame of reference model: Math school grades had positive effects on MSC, but the effects of German grades were negative;

(2) reciprocal effects (longitudinal panel) model: MSC was predictive of and predicted by math test scores and school grades;

(3) big-fish-little-pond effect: The effects on MSC were negative for school-average achievement based on 4 indicators (primary school grades in math and German, school-track prior to the start of secondary school, math test scores in the first year of secondary school).

Results for all 3 theoretical models were consistent across the 5 secondary school years: This supports the prediction of developmental equilibrium. This integration highlights the robustness of support over the potentially volatile early to middle adolescent period; the interconnectedness and complementarity of 3 ASC models; their counterbalancing strengths and weaknesses; and new theoretical, developmental, and substantive implications at their intersections.

Keywords: developmental equilibrium, math self-concept, frame of reference effects, reciprocal effects, big-fish-little-pond effects

An Integrated Model of Academic Self-Concept Development: Academic Self-Concept, Grades, Test Scores, and Tracking Over 6 Years

Self-concept and related self-beliefs are key constructs in developmental and educational psychology. For many developmental researchers, and in many early childhood programs (e.g., Fantuzzo et al., 1996), self-concept has been a “cornerstone of both social and emotional development” (Kagan, Moore, & Bredekamp, 1995, p. 18; also see Davis-Kean & Sandler, 2001; Marsh, Ellis, & Craven, 2002). Academic self-concept (ASC) is also widely accepted as a critical psychological construct that leads to success in educational settings (Chen, Yeh, Hwang, & Lin, 2013; Marsh & Craven, 2006; Marsh & Yeung, 1997), in social and emotional situations (Harter, 2012; Marsh, Parada, Craven, & Finger, 2004, Pekrun, 2006), and in daily life more generally (Eccles, 2009; Elliot & Dweck, 2005).

Before outlining the integrated model, we begin with a brief overview of the contributory theories, three of the most important theoretical models in ASC research, which are as follows:

- The internal/external frame of reference (I/E) model relates math and verbal achievement to corresponding measures of ASC;
- the reciprocal effects model (REM) of relations between academic achievement and ASC over time; and
- the big-fish-little-pond effect (BFLPE), that is the negative effect of school-average achievement on ASC.

Although there is much support for each of these theoretical models considered separately, to our knowledge no study has considered all three models within a unified theoretical framework and a single statistical model incorporating parameter estimates to test all three models simultaneously, using a database suitable for testing all three within a single integrated model.

Historically, the understanding of ASC has been limited by the piecemeal approaches that are endemic when separate theories are considered each in isolation. Thus, for example, the main focus of the I/E model is the juxtaposition of math and verbal constructs; however, this focus on domain specificity is largely ignored in the other two models, which typically are tested within a single

academic domain. Likewise, the focus of the reciprocal effects model is on longitudinal relations of ASC and achievement over time, but this longitudinal perspective is largely ignored by the other two models, which typically are tested using cross-sectional data. The critical feature of the BFLPE model is its multilevel consideration of contextual effects (the effects of school-average achievement on self-concept), but this multilevel perspective is largely ignored by the other two models, which typically are tested with single-level models. Importantly, this integration of ASC theories (hereafter referred to as the integrated ASC model) results in a number of new predictions (see the online Supplemental Materials, Section 7, for new predictions that could not be derived from the individual components of the integrated ASC model when considered separately). To this integration of models we add a developmental perspective, in which we evaluate support for the consistency of effects (which we subsequently refer to as developmental equilibrium) across the potentially turbulent, a period of early to middle adolescence (first 5 years of secondary school) that involves so many biological and psychological changes (e.g., Eccles, 2009; Eccles et al., 1993; Harter, 2012; Steinberg, 2008).

We also note that the integrated ASC model, and empirical tests of the model, are important because each of the three separate theories leaves open the question as to whether the effects hypothesized in one model are independent of the effects hypothesized in the other two. Only the integrated ASC model (and tests of this model) allows us to examine the robustness of the effects considering all predicted effects combined.

The new integrated ASC model (see Figure 1) incorporates the I/E, REM, and BFLPE models, which are based on the theoretical and empirical work of Marsh and colleagues (e.g., Marsh, 2007; Marsh & Craven, 2006; Marsh, Seaton, et al., 2008; Möller & Marsh, 2013). Thus, its overarching aim is to systematically explain the relations between ASC and academic achievement across domains (dimensional comparisons within the I/E model; i.e., “My accomplishments in one domain relative to accomplishments in other domains”), time (development within the REM model; i.e., “My current accomplishments relative to past accomplishments”), and school peer group (social comparisons within the BFLPE model; i.e., “My accomplishments relative to those of my peer group”).

In summary, there are important advantages in bringing these three theoretical models within the unified framework proposed here. The complementarity of these different theoretical perspectives allows us to achieve a broader understanding of the formation of ASC. In addition, integrating the three into a single unified framework results in new theoretical predictions arising from the intersections of the different models (see subsequent discussion). Methodologically, it is also important to emphasize that with appropriate data, all three models can be tested within a single statistical model. We demonstrate how parameter estimates based on one unified statistical model provide tests of each of the three ASC models from a developmental perspective: This reinforces their complementarity.

Integration of Three Theoretical Models of ASC Formation

In the present investigation, we aim to investigate how students develop their beliefs about their competence throughout their adolescence. In pursuing this aim, we take into account three main influences that have been identified in prior research in the three theoretical models, which are as follows: dimensional comparison, reciprocal effects, and social comparison effects.

The I/E Model: Dimensional Comparison Effects

ASCs in specific academic domains are much more differentiated than are the corresponding measures of achievement. Indeed, even though math and verbal achievements tend to be highly correlated, math and verbal self-concepts tend to be nearly uncorrelated (Marsh, 1986, 2007; Marsh, Kuyper, Seaton, et al., 2014). The I/E model provides a theoretical rationale for these seemingly paradoxical results, in positing that ASC in a particular school subject is formed in relation to two comparison processes: an external (social comparison) reference, in which students compare their performances in a particular school subject with the performances of other students in the same school subject, and an internal (dimensional comparison) reference, in which students compare their own performances in that particular school subject with their own performances in other school subjects. In particular, Marsh (1986) proposed that students use an internal comparison process, whereby academic achievement in one domain (e.g., verbal) provides a frame of reference for forming ASC in a contrasting domain (e.g., math).

Although the I/E model posits that achievement is highly positively predictive of ASC in the matching domain, the critical theoretical predictions are the negative cross-paths leading from achievement in one subject to ASC in the other subject; for example, verbal achievement to math self-concept (MSC). The theoretical rationale for the negative cross-paths (dimensional comparisons) is that students will use verbal achievement, for example, as a basis of comparison in the formation of their MSC. Thus, high verbal achievement will detract from a high math self-concept; likewise, students who have good math achievement will have lower MSCs if their verbal achievement is much higher than their math achievement. Following initial tests of the I/E model (Marsh, 1986), the I/E model predictions were found to be supported in 26 countries using Programme for International Student Assessment (PISA) data (Marsh & Hau, 2004). In a subsequent meta-analysis based on 69 data sets, Möller et al. (2009) reported that math and verbal achievements were highly correlated ($r = .67$), but that the corresponding self-concepts were nearly uncorrelated ($r = .10$). The paths from math achievement to MSC were positive ($\beta = .61$), but paths from verbal achievement to MSC were negative ($\beta = -.27$).

(INSERT FIGURE 1 HERE)

The REM of Relations Between ASC and Achievement

ASC and academic achievement are substantially correlated, but a critical question with important theoretical and policy–practice implications is the temporal ordering of these constructs. Traditional approaches to this issue (Calsyn & Kenny, 1977) took an “either-or” approach— either prior achievement leads to subsequent ASC (a skill development model) or prior ASC leads to subsequent achievement (a self-enhancement model). However, integrating theoretical and statistical perspectives, Marsh (1990) argued for a dynamic reciprocal effects model (REM) that incorporates both the skill development and the self-enhancement models, such that both ASC and achievement are posited to be causes and also effects of each other; the REM is testable when both constructs are collected in at least two but preferably three or more waves of data.

In meta-analyses of REM studies, Valentine et al. (2004; also see Huang, 2011) found consistent support for the REM. It is not surprising that prior achievement has an effect on ASC, as this is consistent with ASC theory and research. However, Valentine et al. demonstrated that the effect of

prior ASC on subsequent achievement, after controlling for the effects of prior achievement, was also highly significant overall, and positive in 90% of the studies they considered. However, two limitations of the results summarized in these meta-analyses are addressed here.

First, although REM studies are necessarily longitudinal, most studies are based on one, two or, perhaps, three waves of data, and do not cover an extended developmental period. Here we evaluate support for the REM on the basis of six waves of data covering the early to middle adolescent (late primary school through high school; see subsequent discussion of Figure 1) period: This provides a stronger test of the consistency of effects over the potentially turbulent developmental period.

Second, in REM studies, achievement typically is assessed by standardized tests or school grades—and yet, the different achievement indicators have different implications. School grades are a particularly salient source of feedback to students and their parents, are easily compared among classmates, and have important implications for academic careers. Hence, school grades tend to be more correlated with ASCs than they are with test scores (e.g., Marsh, Kuyper, Morin, et al., 2014; Marsh, Kuyper, Seaton, et al., 2014; Marsh, Trautwein, et al., 2005). However, school grades typically are idiosyncratic to specific teachers, settings, and schools. In particular, teachers typically grade on a curve, allocating the highest and lowest grades to the relatively best and least- well performing students within a classroom, respectively. Hence, teachers use the classroom as a narrow frame of reference in their grading procedure, largely ignoring the absolute levels of achievement of students in their class based on a common metric that generalizes over all students. Although the classic meta-analyses support REM predictions in respect of both school grades and test scores, most individual studies have included only one of these indicators of achievement, and apparently none have juxtaposed the two over such an extended developmental period as that considered here or in relation to developmental perspectives. Furthermore, incorporating both verbal and math test scores into the integrated ASC model integrates the typically cross-sectional tests of the I/E model with the reciprocal effects inherent in the REM, and the multilevel effects of school-average achievement in BFLPE studies.

The BFLPE: Social Comparison Effects

According to the BFLPE, students compare their own academic achievement with the achievements of their classmates, and use this social comparison as the basis of their ASCs (Marsh, Kuyper, Morin, et al., 2014; Marsh, Abduljabbar, et al., 2015; Marsh & Parker, 1984; Marsh, Seaton, et al., 2008; Nagengast & Marsh, 2012; Zell & Alicke, 2009). In the BFLPE, students who attend high-ability schools tend to have lower ASCs than do equally able students who attend mixed- or low-ability schools, which is a negative effect of school-average achievement on ASC.

There is now considerable support for the negative effects of school-average achievement on ASC (see reviews by Marsh, Seaton, et al., 2008; Marsh & Seaton, 2015). Demonstrating that the BFLPE is one of psychology's most cross-culturally universal phenomena, three successive Programme for International Student Assessment (PISA) data collections (Marsh & Hau, 2003: 103,558 students from 26 countries; Seaton, Marsh, & Craven, 2010: 265,180 students from 41 countries; Nagengast & Marsh, 2012: 397,500 students from 57 countries) showed that the effect of school-average achievement on ASC was negative in all but one of the 123 samples, and significantly so in 114 samples. Further, not only does the BFLPE tend to increase in size during the period that students attend the same high school (Marsh, Köller, & Baumert, 2001), but Marsh, Trautwein, Lüdtke, Baumert, and Köller (2007) have shown that the BFLPE formed in high school is equally large, or larger, two (Study 1) and four (Study 2) years after graduation from high school. Similarly, Marsh and O'Mara (2008; Guo, Marsh, Parker, & Morin, 2015) showed that ASC formed in high school contributed to the prediction of long-term educational attainment eight years later, and beyond the effects of school grades, standardized achievement tests, IQ, and socioeconomic status. Nevertheless, BFLPE studies have several limitations; these are addressed in the present research.

First, most BFLPE studies are cross-sectional, so that the school-average achievement associated with a particular school might reflect either the ability of students prior to attending that school, or the subsequent effects of the school on achievement— potentially confounding the temporal ordering. Second, the primary focus on school-average achievement as a measure of de facto selectivity (e.g., selectivity based on neighborhood) might not generalize to explicit selectivity when students are tracked into different schools on the basis of prior achievement (see Marsh, Köller, & Baumert, 2001).

Third, because school grades typically do not reflect a common metric, previous BFLPE studies have been based on test scores rather than on school grades. However, school grades are a more salient measure of achievement than are standardized test scores, influence ASCs more than test scores do, and are often an important basis for tracking students. Nevertheless, because of the grading on a curve effect, school-average grades are unlikely to be comparable over schools when schools differ in terms of mean achievement levels. Finally, BFLPE studies traditionally evaluate school-average achievement in the same domain as the corresponding measure of ASC (e.g., the effects of school-average math achievement on MSC). However, integrating the I/E and BFLPE leads to the question of how school-average achievement in a contrasting domain might affect ASC (i.e., the effect of school-average verbal achievement on MSC). Given the unique design of our study, we were able to address each of these limitations of prior BFLPE research by integrating different theoretical and developmental perspectives.

Integrating Developmental Equilibrium into the Integrated ASC Model

Developmental equilibrium. Our study is based on testing the empirical support for what has been referred to as developmental equilibrium (Marsh, Craven, et al., 2016; Marsh, Pekrun, Lichtenfeld, et al., 2016; Marshall et al., 2015; see the online Supplemental Materials, Section 1, for further discussion). Although the term equilibrium comes from the physical sciences, it has long been applied as an analogous concept in psychological theorizing—particularly in developmental psychology. Equilibrium is reached when a system achieves a state of balance between potentially counterbalancing, opposing forces (e.g., physiological homeostasis, Cannon, 1932; psychological equilibrium balancing competing drives and desires, Argyle, 1967; Erikson, 1974; self-actualization as an equilibrium between actual and ideal self-perceptions; Rogers, 1961). In child development, Piaget and Cook (1952) argued that the psychological system aims to achieve a steady state of equilibrium that allows children to accommodate new experiences using existing schemas, whereas disequilibrium forces children to change their cognitive structures to regain equilibrium. In each of these different perspectives on equilibrium, the critical issue is that of balance, posited to be a psychologically desirable state, and indicating consistency over time.

Here we evaluate support for developmental equilibrium through tests of the consistency of relations among critical variables over early to middle adolescence—that is, whether the self-system is consistently in a state of balance during this period. Thus, for example, Davis-Kean et al. (2008; also see Davis-Kean, Jager, & Collins, 2009) reported that the relation between ASC and achievement changed with age for young children, but became relatively stable from the age of about 12. This suggests that this relation is stable and has reached a state of equilibrium during the early to middle adolescent period, which is the focus of our study.

Although the term is often used metaphorically, achieving a state of equilibrium clearly has important substantive and psycho- logical implications. Here, however, we operationalize this perspective by integrating it with formal statistical models of longitudinal invariance, based on models of the invariance of effects across multiple waves of data. This has theoretical, developmental, and substantive implications: for example, the question of whether the effect sizes of critical components in each of these models of ASC formation vary developmentally (Eccles, 2009; Marsh, 2007; Marsh & O'Mara, 2008; Marsh, Seaton, et al., 2008; Murayama et al., 2013), including the relative sizes of paths leading from achievement to ASC, and ASC to achievement in the REM; the size of the BFLPE; and the strength of the internal comparison process in the I/E model. In summary, our major developmental focus is on tests of developmental equilibrium: the consistency over time of relations between ASC and achievement in reference to predictions from the three theoretical ASC models, over the potentially turbulent period of early to middle adolescence (e.g., Eccles, 2009; Eccles et al, 1993; Harter, 2012; Steinberg, 2008).

We also note that our notion of developmental equilibrium closely resembles Fraley, Roisman, and Haltigan's (2013) "Legacy of Early Experiences in Development," which they present as an important, ongoing debate in developmental science. Specifically, they argue: "By studying the pattern of associations across time, it should be possible to gain greater insight into the legacy of early experiences" (p. 113). Indeed, their paradigmatic models closely resemble our integrated ASC model (see Figure 1). They proposed models of the longitudinal effects of a particular event in time that are similar to our evaluation of primary school grades and school-average ability. Their emphasis, like ours, was on the direct and indirect effects of a variable over time. However, as in our evaluation of

the REM, they also proposed cross-lagged panel models of the same variables measured on multiple occasions over time. In- deed, our a priori hypothesis of developmental equilibrium can be seen as a special case of a more general model, in which selected effects are consistent over time—a possibility that they introduced by testing the equality of parameter estimates across multiple waves of data. Like us they argued for consideration of more than two waves of data in which the same constructs are studied—ideally, covering an important developmental period. Further, their study, like ours, integrates multiple models into a single theoretical and statistical framework.

Conceptual implications and new theoretical predictions. Given the importance of studying the consistency of patterns of associations over time (Fraley et al., 2013), we sought to test the consistency of support for predictions from each the ASC models over the critical early to middle adolescent period. The I/E model is the best-known system of knowledge that captures both the social and the dimensional comparison processes that give rise to the ASC. In contrast, the REM model represents the theoretical implications of self-concept for the critical outcome of achievement. Intriguing paradoxical hypotheses arise from the integration of these theoretical models: In the I/E model, MSC is positively predicted by math achievement but negatively predicted by verbal achievement (the dimensional comparison process). This suggests, perhaps, that verbal self-concept might also have a negative effect on subsequent math achievement (in contrast to the positive effect of MSC; Parker, Marsh, Morin, Seaton, & Van Zanden, 2015). Although this untested hypothesis appears counterintuitive, it follows directly from the theoretical integration of the I/E and the REM.

Next, we consider the place of the BFLPE within this integrated system. Unlike the REM and, perhaps, the I/E model, the BFLPE is the result of a particular event at a given point in time—namely, school selection—and thus can be considered as distinct from the integrated I/E and REM's operation within high school. Thus, unlike the REM and the I/E, the BFLPE can be seen as a response to an age-graded developmental task. Specifically, at age 10, children in Germany are sorted into different academic tracks and into schools of different average ability. This sorting of children in relation to prior achievement thus determines a child's relative position within their peer environment and subsequently, the influence of the school context on their self-concept (i.e., the BFLPE). The question then is what role this early developmental experience plays in the REM I/E system. Several

possibilities are suggested by Fraley et al. (2013). First, the effect could be initially impactful, before trailing off over time. This might be the case if initial position within the school becomes less important for self- concept over time. In this case, we would expect the effect of school average achievement on ASC to decline over time. Should this be so, the need to address the BFLPE, to arrest poor ASC and its effect on performance, might take on less practical and research significance.

Alternatively, the BFLPE could have an enduring or even increasing effect, such that school placement might assume even more prominence, due to its enduring effect on ASC. Likewise, from the perspective of the REM model, school placement might have an increasing effect, due to its influence on subsequent achievement. Furthermore, and given the I/E model, school- average achievement in one subject might have contrasting effects on ASC and achievement in other subjects.

Taken together then, this research considers the legacy of school selection (as per the BFLPE) on the system of ASC given by the integration of the I/E and REM effects. These new research issues and other benefits come from the heuristic integration of the different models into a unified conceptual framework of self- concept formation. (Also see the online Supplemental Materials Section 7 for other examples of new predictions based on the integrated ASC model.)

Methodological and design implications. Appropriate analysis of the integration of the ASC (I/E, REM, and BFLPE) models and developmental perspectives requires large, representative, longitudinal samples of students from many different schools. Particularly in BFLPE studies, appropriate multilevel models are required that also take into account the nesting of students within schools. Likewise, in REM studies, at least two and preferably many more than two waves of data are required, to test reciprocal effects between ASC and achievement, whereas in the I/E model it is important to contrast ASCs and achievement in at least two domains—typically, math and verbal. Statistical tests of developmental equilibrium require that the same set of variables be collected in at least three waves of data that span a critical developmental period of interest.

Due in part to methodological and design features that are idiosyncratic to each, research into each of these theoretical models has developed somewhat in isolation of the others. Methodologically, constraining paths to be equal (our test of developmental equilibrium) has statistical advantages (e.g., model identification, convergence, improved parsimony, increased statistical power, ease of

interpretation) that are completely aside from the substantive meaning associated with support for developmental equilibrium. Although individual studies, and particularly meta-analyses of the three models of ASC, evaluate the consistency of effects over different age groups, this is rarely based on true longitudinal data in which the same set of variables is administered to the same individuals over an extended developmental period. Extending research into each of these ASC models, we posit new developmental perspectives on each through the integration of all three into a single study. From a developmental perspective, appropriate longitudinal data, strong theoretical models, and appropriate statistical analyses are important in testing the consistency of support for predictions over critical stages of development, such as the potentially turbulent years of early to middle adolescence considered here.

The Present Study: A Priori Research Hypotheses and Research Questions

Here we integrate and extend three major ASC models (REM, I/E, and BFLPE) to form an integrated ASC model in a longitudinal study of developmental equilibrium. Data (a representative sample of 3,370 students from 42 schools) were collected from the year before the start of secondary school (Year 4 school grades in German and math) and in each of the subsequent 5 years of compulsory secondary schooling in Germany (math school grades, standardized math achievement tests and MSCs). We seek to demonstrate that the three theories of self-concept formation, developmental equilibrium, and appropriate statistical methodology can be unified in a single model, as presented in Figure 1.1

Hypothesis 1: I/E Model—Paths From Year 4 Variables to Variables in Years 5 Through 9

In Figure 1, paths (dashed lines) from primary-school math grades (Year 4) to MSC (Year 5) are predicted to be positive, but those leading from primary-school German grades (Year 4) to MSC (Year 5) are predicted to be negative (noting however, that we cannot test the corresponding paths to German self-concept, because we do not have measures of German self-concept). We leave as a research question whether there are direct effects of primary-school grades on subsequent MSCs (e.g., the effect of primary grades on MSC in Years 6 through 9 after controlling for the effects of math test scores, school grades in math, and MSCs in Year 5). However, in support of developmental equilibrium, we hypothesize an enduring legacy of the effects of achievement at the end of primary

school on outcomes across secondary school years: that the total effects of primary-school grades are invariant over the multiple waves of data.

Hypothesis 2: REM—Paths Relating Variables in Years 5 Through 9

Consistently with REM research, we posit that paths leading from prior achievement to subsequent MSC (e.g., paths leading from test scores and school grades in Year 5 to MSC in Year 6) will be positive, as will be paths leading from prior MSC to subsequent achievement. In support of developmental equilibrium, these lag-1 paths (i.e., paths from variables in one wave to the immediately next wave in Figure 1; also see the Fraley et al., 2013) are predicted to be consistent over all five waves.

Hypothesis 3: BFLPE: School-Average Achievement Effects on MSC in Years 5 Through 9

Consistently with previous BFLPE theory and research, we predict that school-average achievement, operationalized in a variety of ways, will have a negative predictive effect on ASC measured in each of the first 5 years of secondary school. However, several features of our study contribute to the unique perspective on this issue that extends previous research. Most BFLPE studies (Marsh, Seaton, et al., 2008; Marsh & Seaton, 2015) evaluate de facto selection (e.g., naturally occurring differences in school-average achievement on the basis of geography or post-code) on the basis of the school-average test scores at some point in secondary school, and relate this contextual variable to ASCs collected in the same school year.

As such existing BFLPE research has several potential limitations that we were able to address in this research. Thus, in our T1 integrated ASC model (Table 1 and Figure 1), school-average math achievement is represented as a latent variable defined by three distinct contextual variables: the traditional BFLPE measure of school-average achievement based on test scores in the first year of secondary school (Year 5, based on tracked schools); school track (high, medium, or low), based on student accomplishments prior to the start of secondary school; and school-average math grades, based on the last year of primary school. However, due to the methodological and theoretical differences associated with each of these contextual measures, we also each of them separately.

We hypothesize an enduring and important legacy of the negative effects of school-average achievement at the end of primary school on MSC outcomes across secondary school years. More

specifically, the developmental equilibrium proposal leads to the prediction that the total effects of school-average achievement at the start of secondary school are consistent in size across the ensuing years of secondary education. However, we also note that there is an apparent clash between this prediction and previous research showing that the BFLPE increases in size the longer students are in the same school (e.g., the BFLPE should be most negative in Year 9). Hence we leave the juxtaposition of these two contrasting predictions as a research question, but note that both are consistent with the hypothesis that the BFLPE has an enduring, negative legacy.

(INSERT TABLE 1 HERE)

A unique aspect of our study, arising from the integration of the BFLPE and I/E models, is the juxtaposition of effects of school-average math and verbal achievement, based on primary school grades, on subsequent MSC during the next 5 years of high school. Because both math and German contribute substantially to tracking decisions, it might be expected that the effects of school-average measures would have similar results. However, the I/E model suggests that at the individual student level, the effects of math and German grades would be in opposite directions. Extrapolating from this I/E-logic, it may be that school-average German achievement has a positive effect on MSC (in contrast to the negative effects of school-average math achievement on MSC). Hence, we leave as a research question whether the effects of school-average math grades in Year 4 on MSC differ substantially from those of school-average German in Year 4 on MSC.

Hypothesis 4: Developmental Equilibrium: Consistency of Paths Over Time (Years 5 Through 9)

Consistently with predictions based on developmental equilibrium, the critical features of our a priori model are the stability- and cross-paths in Figure 1.

1a. Autocorrelation paths. All autocorrelation (test–retest, horizontal) paths relating all Years 5 through 9 variables in each wave to the same variable in the subsequent wave (see Figure 1) are expected to be invariant across waves (e.g., all lag-1 stability paths for MSC measured in one wave to MSC measured in the next wave are constrained to be the same across all five waves).

1b. Cross-paths. Cross-paths relating all variables in Years 5 through 9 in each wave to each of the different variables in subsequent waves (see Figure 1) are also expected to be invariant across

waves (e.g., lag-1 paths from test scores in Year 5 to MSC in Year 6 are the same as the lag-1 path from test scores in Year 8 to MSC in Year 9). These cross-paths in our integrated ASC model are of particular importance in testing predictions for the three theoretical ASC models that are based on the cross-paths. In particular, tests of the invariance of cross-paths provide a very strong test of developmental equilibrium and the consistency over time of predictions based on these theoretical models.

Method

Sample

The data in our study were based on the Project for the Analysis of Learning and Achievement in Mathematics (PALMA; Frenzel, Pekrun, Dicke, & Goetz, 2012; Marsh, Pekrun, Lichtenfeld, et al., 2016; Marsh, Pekrun, Parker, et al., 2016; Murayama et al., 2013; Murayama et al., 2016; Pekrun et al., 2007; Pekrun, Lichtenfeld, Marsh, Murayama, & Goetz, 2017), a large-scale longitudinal study investigating the development of math achievement and its determinants during secondary school in Germany. The study was conducted in the German federal state of Bavaria and consisted of five measurement waves spanning Years 5 to 9 in secondary school (the last 5 years of compulsory education), as well as school grades from the last year of primary school (Year 4). A unique aspect of our study that derives from the nature of the German school system is that the primary schools considered here, in contrast to the secondary schools, were not tracked, and thus were relatively heterogeneous in relation to achievement in Year 4 (prior to the start of secondary school). Primarily on the basis of primary school performance, starting in Year 5, students are tracked into three school types that are relatively homogeneous in relation to achievement: high-achievement (Gymnasium), middle-achievement (Realschule), or low-achievement (Hauptschule) school tracks.

Excluding a small number of students for whom tracking was not introduced until Year 7 rather than Year 5, students ($N = 3,450$; 50% girls; M age = 11.7 at Year 5, $SD = 0.7$), the sampling design resulted in a representative sample of students in Bavaria, in terms of student characteristics (e.g., gender, urban vs. rural, socioeconomic status; see Pekrun et al., 2007). At the first assessment (Grade 5), the sample comprised 2001 students. In each subsequent year, the study not only tracked the children who had participated in previous assessments, but also included those children who had not

yet participated in the study but had become children of PALMA classrooms at the time of the assessment (see Pekrun et al., 2007), resulting in sample sizes of 1,992 (Year 6), 2,327 (Year 7), 2,342 (Year 8), 8; and 2,461 (Year 9) 2,461. Due in part to this sampling design, a substantial portion of the sample had missing data for at least one of the measurement waves. Across the five waves, 38% participated in all five measurement waves (i.e., Grades 5 through 9), and 9%, 19%, 15%, and 19% took part in four, three, two, or one of the assessments, respectively.

Students answered the questionnaire toward the end of each successive school year. All instruments were administered in the students' classrooms by trained external test administrators. Participation in the study was voluntary and parental consent was obtained for all students. Agreement was high (100% for schools and over 90% for students at each data wave), and the final sample closely represented the intended sample and population more generally (Pekrun et al., 2007). Surveys were identified by an anonymous code number to ensure participant confidentiality.

Measures

MSC was measured in each of the five secondary schools (Years 5 through 9) with the same set of six items, using a five-point Likert scale, ranging from not true, hardly true, somewhat true, largely true, to absolutely true. Across the five waves, the alpha estimates of reliability were consistently high (Year 5 $\alpha = .88$; Year 6 $\alpha = .90$; Year 7 $\alpha = .89$; Year 8 $\alpha = .91$; Year 9 $\alpha = .92$). The items used to measure MSC were as follows: "In math, I am a talented student"; "It is easy for me to understand things in math"; "I can solve math problems well"; "It is easy to me to write tests/exams in math"; "It is easy to me to learn something in math"; "If the math teacher asks a question, I usually know the right answer".

Students' achievement was measured with school grades (math in Years 4 through 9; German in Year 4) and math standardized achievement test scores (Years 5 through 9). School grades were end-of-the-year final grades obtained from school documents. The standardized PALMA Math Achievement Test (Murayama et al., 2013; Pekrun et al., 2007) was based on multiple-choice and open-ended items to measure students' modeling and algorithmic competencies in arithmetic, algebra, and geometry. The test was constructed using multimatrix sampling with a balanced incomplete block design, such that the number of items increased with each wave, varying between 60 and 90 items

across the five waves, with anchor items to allow for linking the two test forms and the five measurement points. The obtained achievement scores were scaled using one-parameter logistic item response theory, confirming the unidimensionality and longitudinal invariance of the test scales (Murayama et al., 2013).

Statistical Analyses

All analyses were done with Mplus 7.3 (Muthén & Muthén, 2008–2015). We used the robust maximum likelihood estimator, which is robust against any violations of normality assumptions. All analyses were based on multilevel models (type = two level in Mplus) using manifest variables (Lüdtke, Marsh, et al., 2008; Marsh, Lüdtke, et al., 2009). Specifically, students were nested within schools, resulting in the nonindependence of observations. Ten imputed data sets were created using the default model in Mplus (see earlier discussion of the sampling design), which included all variables used in the analyses, including school- average measures of math achievement and also student back- ground variables (i.e., socioeconomic status, gender, IQ). The final parameter estimates and fit statistics were obtained through the aggregation procedure implemented in Mplus, following Rubin's (1987) rules.

To facilitate interpretation of parameter estimates and tests of developmental equilibrium, we standardized all measures. As the standardized math test varied from year to year, test scores were standardized separately for each year. For school grades and self- concept responses that varied along a common metric, all measures were standardized in relation to values at Wave 1 (Year 5; see the online Supplemental Materials, Section 2), resulting in a standard effect size metric in relation to standard-deviation units. Particularly in longitudinal cross-lagged studies covering such a substantial period of time with many waves of data, it is important to distinguish between direct effects (the path coefficients in traditional path models) and total effects (the sum of these direct effects and the indirect effects that are mediated through intervening variables).

Developmental Equilibrium: Rationale for the Final Integrated ASC Model

In tests of developmental equilibrium, we conducted formal tests of the invariance of paths leading from one wave to the next, across all waves. To conserve space and maintain a focus on substantive issues, the detailed models in support of developmental equilibrium and related statistical

issues are presented in the online Supplemental Materials, Sections 1 and 3, and summarized here briefly.

The pattern of path coefficients is determined in part by the number of lags included (see Figure 1). Thus, lag-1 paths are from a variable in one wave to a variable in the next wave, whereas lag-4 paths are from a variable in Wave 1 (Year 5) to a variable in Wave 4 (Year 9). The rationale for including paths greater than lag-1 was based on a mix of theoretical and empirical results. A priori, there is no reason why a model with only lag-1 paths should be the best model (see related discussion by Fraley et al., 2013, who also propose that models with paths greater than lag-1 should routinely be considered). If additional paths are needed to achieve a good fit, then constraining them to be zero is likely to bias the results and the interpretation of the lag-1 paths. Hence, the theoretically more conservative approach is to include additional paths unless there is clear evidence that they are not needed.

Our final model (see Figure 1) included the following paths: from Year 4 (the last year of primary school) to all subsequent variables in the next 5 years (the first 5 years of secondary school); autocorrelation (horizontal) test-retest paths from variables (Years 5 through 9) in one wave to variables in subsequent waves (lags 1 through 4); cross-paths from measures (Years 5 through 9) of one construct to a different construct in the next two waves (lag-1 and lag-2 paths). In preliminary analyses (see Models 1 through 4 in the online Supplemental Materials, Section 3), we explored how many lags were needed to fit the data. Models with only lag-1 paths provided a poor fit to the data. Inclusion of paths from the two primary school (Year 4) variables to all variables in Years 5 through 9 (rather than only lag-1 paths to just the Year 5 variables) improved the fit. However, Model 4 (with lags 1 through 4 autocorrelation paths but only lag-1 and lag-2 cross paths) provided an excellent fit to the data (see the online Supplemental Materials, Section 3); this is consistent with our supposition that more than lag-1 paths are needed. This model with multiple lags is also conservative, providing stronger controls for preexisting differences, particularly compared with the typical approach used in developmental studies, which are based on only two waves of data, and studies with more than two waves of data that ignore paths other than lag-1 effects.

In Model 5 (see the online Supplemental Materials, Section 3), we added invariance constraints to Model 4 to test the a priori assumption of developmental equilibrium (that the paths are consistent over waves). In Model 5, there was strong support for complete invariance of autocorrelation- and cross-paths, across all waves. This included the invariance of cross-paths (e.g., MSC wave_i → Test Scores wave_{i+1} = MSC wave_{i+1} → Test scores_{i+2}), which are central to tests of predictions from our three theoretical models of ASC formation. However, autocorrelation paths for Lag 1 through 4 paths were also shown to be invariant. For example, not only were lag-1 paths invariant (e.g. MSC wave_i → MSC wave_{i+1} = MSC wave_{i+1} → MSC wave_{i+2}), but also lag-2 paths (e.g. MSC wave_i → MSC wave_{i+2} = MSC wave_{i+1} → MSC wave_{i+3}), lag-3 paths and lag-4 paths were also invariant. The fit of Model 5 was excellent, and differed little from that of Model 4 with no invariance constraints; this provides support for the more parsimonious model. In the final model in this sequence (i.e. the integrated ASC model; see the online Supplemental Materials, Section 3), we added three school-level variables (school-average math grades from Year 4, school track, and school-average test scores) that defined a latent variable used to infer school-average achievement. This model provided an excellent fit to the data and provided the basis for all subsequent analyses. This latent factor of school-average achievement was well-defined (e.g., standardized factor loadings for the three indicators varied from .94 to .98) and inclusion of the factor at the school level actually resulted in a marginally better fit to the data, relative to the model with no school-level factors (see the online Supplemental Materials, Section 3). Finally, we repeated all the analyses leading up to the final model, including the latent school-average achievement factor to the final model (see the online Supplemental Materials, Section 3), demonstrating that this did not alter conclusions about the structure of the model at the student level.

This final multilevel model (see Figure 1 and Table 1; also see the online Supplemental Materials, Section 3, for further discussion) is referred to as the integrated ASC model because parameter estimates from this one statistical model provide tests of a priori predictions in relation to the internal/external frame of reference model (Hypothesis 1), the reciprocal effects model (Hypothesis 2), and the big-fish-little-pond effect (Hypothesis 3). Support for the invariance of path coefficients over Years 5 through 9 (the first 5 years of secondary school), demonstrated through tests of

developmental equilibrium, provides an important developmental perspective on each of the ASC models considered here. Thus, the invariance of parameter estimates over time provides support for developmental equilibrium in respect of each of the ASC models (Hypotheses 1 through 3), as well as developmental equilibrium more generally.

Results

The latent correlation matrix among student-level variables (see the online Supplemental Materials, Section 2) provides an advanced organizer in relation to subsequent analyses. Math test scores in secondary school (Years 5 through 9) were substantially and consistently correlated across the 5 years for both primary school (Year 4) math grades ($r_s = .65$ to $.70$) and German grades $r_s = .48$ to $.57$). Interestingly, these correlations of primary school grades with secondary school test scores were substantially higher than corresponding correlations between test scores and school grades in secondary school ($.26$ to $.43$). This is consistent with earlier discussion, and suggests that school grades in un-tracked primary schools are more like test scores, in that they reflect a more common underlying metric continuum than do grades in Years 5 through 9 in the highly tracked secondary schools. These results have potentially important implications for understanding the grading on a curve phenomenon (see Supplemental Materials, Section 2, for further discussion), as well as our subsequent use of school-average achievement based on these Year 4 math grades. Finally, consistent with much previous research, correlations between MSC and school grades ($r_s = .42$ to $.62$) are higher than the corresponding correlations between MSCs and test scores ($r_s = .30$ to $.34$).

Frame of Reference Effects: The I/E Model (Hypothesis 1)

In tests of the I/E model, our focus is on the dashed paths in Figure 1, reflecting the effects of primary school grades (Year 4) on subsequent measures of MSC collected during secondary school (Years 5 through 9). Tests of this model are based on our T2 integrated ASC model (see Table 2). Consistent with the I/E model and Hypothesis 1, the path from Year 4 math grades to MSC in Year 5 is significantly positive ($.49$, Table 2), whereas the path from Year 4 German grades to Year 5 MSC is significantly negative ($-.26$).

As noted previously, in evaluating the consistency of effects of Year 4 grades over MSC in Years 5 through 9 we focus on total effects (but present both total and direct effects in Table 2). The total

effects of Year 4 Math grades on MSCs in Years 5 through 9 were consistently positive (paths = +.48 to +.54) and were not significantly different from each other (Wald test [$df = 4$] = 8.195, $p = .085$). In contrast, the total effects of Year 4 German grades on MSCs (paths = -.25 to -.29) in Years 5 through 9 were consistently negative, but again were not significantly different from each other (Wald test [$df = 4$] = 1.179, $p = .703$). In summary, there is strong support for the I/E model and for the developmental equilibrium hypothesis, on the basis of the consistency of the effects of Year 4 grades across MSC in Years 5 through 9.

It is also informative to evaluate the direct effects of Year 4 grades on Years 5 through 9 outcomes, controlling for intervening variables (noting that both the direct and total effects are based on Model 7). The question then becomes what are the direct effects of Year 4 school grades on, for example, Year 9 MSC after controlling for the indirect effects that are mediated through MSC, math school grades, and math test scores from Years 5 through 8 (the direct paths in Table 2 are the same as those presented in Table 1, but are repeated to facilitate the comparison of direct and total effects in Table 2). Beyond Year 5, the direct effects of Year 4 math grades continue to be significantly positive for Year 6 MSC (.18), in addition to the positive effects on Year 5 MSC (path = .49), whereas paths to MSC in Years 7 through 9 are nonsignificant. Of course, in subsequent Years 6 through 9, there are still substantial total effects of Year 4 math grades, but these are mediated through outcomes in intervening years.

The pattern of results based on Year 4 German grades is different. In addition to effects on MSC at Year 5, there are new, statistically significant negative direct effects on MSCs in Years 5 through 8 (-.20, -.12, and -.08, respectively). It is only in Year 9 that the negative effects of Year 4 German grades are no longer statistically significant. These new effects of Year 4 German grades in Years 7 and 8 are likely to be due to the fact that intervening variables during secondary school years did not include measures of German achievement, which would otherwise mediate the effects of Year 4 German grades, as was the case with Year 4 math grades.

(INSERT TABLE 2 HERE)

REM: Temporal Ordering of School Grades, Test Scores, and MSC (Hypothesis 2)

In evaluating the temporal ordering of ASC and achievement, we focus on lag-1 cross-paths relating MSC and math achievement (see Figure 1). The results are consistent with the REM (Hypothesis 2): For our integrated ASC model (see Table 3; also see Figure 1 and Table 1), paths are positive leading from prior MSC to subsequent achievement (school grades, .07, SE = .01; and test scores, .04, SE = .01) and from prior achievement to subsequent MSC (school grades, .14, SE = .02; and test scores, .11, SE = .02). The reciprocal effects associated with school grades were significantly higher than were those for test scores (Wald = 9.761, df = 2, p = .008). This also is consistent with previous research, although these differences were surprisingly small (see Table 3). In additional models (see Table 3) we also tested the effects of grades (without test scores) and test scores (without grades). Not surprisingly, when both school grades and test scores were considered separately, the sizes of the reciprocal effects between achievement and MSC were somewhat higher. However, the pattern of results was similar, in that all reciprocal effects were significantly positive.

(INSERT TABLE 3 HERE)

BFLPE: Negative Effects of School-Average Achievement (Hypothesis 3)

In support of this hypothesis and extensions of the BFLPE over the five secondary school Years 5 through 9 (see Figure 1), we begin with the integrated ASC model (see Table 4) in which T4 school-average achievement is based on a latent factor defined by school-average math Year 4 grades, school-average test scores, and school track. This latent factor was well-defined, as correlations among the three indicators varied from .89 to .94, and the standardized factor loadings varied from .94 to .98. The direct effects were significant in Year 5, but were not significant in Years 6 through 8, indicating that the initial negative effects in Year 5 neither increased nor decreased during these years. However, there was a significantly negative direct effect in Year 9, indicating that the BFLPE is significantly more negative in Year 9, even after controlling for the negative effects in Years 5 through 8. This indicates that following the significant negative effect in Year 5, there is no significant change in the size of the BFLPE over the period of Years 6 through 8, but there is a new,

significantly negative BFLPE at Year 9 beyond what can be explained in terms of the effects in Years 5 through 8.

This pattern of results for the direct effects is consistent with the finding that the total effects were statistically significant in all Years 5 through 9 ($-.13$ to $-.26$). The test of the equality of the total effects was rejected (Wald = 21.73, $df = 4$, $p < .001$), but orthogonal polynomial contrasts were nonsignificant for both linear and quadratic effects. However, comparisons of the total effect for each year against the mean effects for the other 4 years revealed only one statistically significant difference: the negative BFLPE was significantly smaller at Year 8 ($-.13$, $p = .008$; see Table 3). Interestingly, although the size of the BFLPE was most negative in Year 9 ($-.31$), this effect was not significantly different from the average total effects in Years 5 through 8 ($p = .132$). In summary, on the basis of the total effects, the direction of the BFLPE was reasonably consistent over the 5 years. Although the Predictor test only most negative effect was in the final year of mandatory school, the nonsignificant linear trend suggests that the effects were not systematically increasing or decreasing over this critical developmental period. Hence, there is clear support for Hypothesis 3: that there is an enduring negative legacy of the BFLPE.

Effects of different indicators of school-average math achievement and school track. In Models A1 through A3 (see Table 3), we tested the BFLPE separately for: school-average achievement based on Year 4 math grades (Model A1), school track (Model A2), and math test scores (Model A3). Not surprisingly, given the very high correlations among these different indicators, the pattern of results based on each is similar to that which is based on the latent factor already discussed. However, this consistency across the three indicators is important, as two of the indicators are based on primary school performance prior to the start of secondary school. In contrast to these true pretreatment indicators, most previous BFLPE studies are based on posttreatment measures of achievement—as with our school-average measure of math test scores.

Next, we juxtaposed the effects of school-average achievement based on math grades (Model A1) with those based on German grades (Model B1). The critical finding is that the negative BFLPEs for school-average German grades are nearly the same as those based on math grades. Again, this is not

surprising, in that the correlation between these two school-average measures ($r = .983$) is very high, such that contextual effects associated with math and verbal performances could not be distinguished.

(INSERT TABLE 4 HERE)

Discussion

The present investigation is a large, longitudinal panel study covering the period from the end of primary school through the first 5 years of secondary school (the end of compulsory schooling in Germany). The study uniquely integrates three of the main theoretical models in ASC research (REM, I/E, BFLPE) and offers new developmental perspectives on each. It does so, in part, by capitalizing on a characteristic feature of the German school system, in which students attend nonselective primary schools up to Year 4, but subsequently attend highly achievement-tracked secondary schools. A critical feature of this study is the longitudinal design, covering the last year of primary school and the first 5 years of secondary school, which provides a unique developmental perspective on the consistency and robustness of effects over this critical early to middle adolescent period. In particular, there was strong support for a very demanding test of developmental equilibrium, demonstrating that support for each of the three theoretical ASC models was highly robust in the developmental period. Importantly, this support for developmental equilibrium is based on an overarching conceptual and methodological framework in which all the predictions are tested in relation to parameters from a single statistical model. The integration is also heuristic in providing new research questions, some of which were tested here, while others remain directions for further research. We now provide a summary of critical new substantive findings, emphasizing the significance of this integration of the three theoretical models and developmental equilibrium into a common conceptual and methodological framework.

Integration of the I/E Model, REM, and Developmental Equilibrium

Tests of the I/E model are traditionally based on a single wave of data and focus on paths leading from achievement to ASC, thus confounding the temporal ordering of ASC and achievement, which is a salient feature of the REM. The integration of the I/E model with the REM and developmental equilibrium resolved this issue in demonstrating the effects of math and German school grades from the end of primary school on math constructs over the next 5 years of secondary school. The effects of

math grades on subsequent MSCs were substantial and positive, whereas the effects of German grades on subsequent MSCs were substantial and negative. This is consistent with the I/E model. In keeping with our developmental equilibrium perspective, the total effects of Year 4 grades on MSCs were remarkably consistent over the next 5 years of secondary school. The consistency of these effects over such an extended developmental period is apparently unique in I/E studies; it suggests that the I/E effects are robust and that this pattern of relations has achieved developmental equilibrium over this period.

The temporal ordering of academic achievement and ASC has important theoretical and policy-practice implications, but most REM studies are based on only two waves of data, neither of which provides tests of developmental equilibrium or of generalizability over critical developmental periods. Our investigation is one of the few to have considered as many as six waves of data—including school grades from before the start of high school. In support of developmental equilibrium, the effect of MSC in one school year to achievement (school grades and test scores) in the next year is similar across all five waves, as is the effect of achievement on MSCs in the following wave.

This pattern of results in support of the REM was consistent over test scores and school grades considered separately or in combination. Although the reciprocal effects associated with school grades were significantly stronger than were those for test scores, it is surprising that these differences were not even larger. Indeed, inspection of the correlations (see the online Supplemental Materials, Section 2) shows that for all Years 5 through 9, MSCs are substantially more correlated with school grades (.42 to .62) than with test scores (.30 to .34). The apparent explanation is that controlling for school grades at Year 4 reduced the effects of subsequent school grades more than the effects of subsequent test scores. Hence, in unreported, supplemental analyses that did not control for Year 4 grades, the reciprocal effects associated with both grades and test scores increased substantially, but the increases for reciprocal effects associated with grades were substantially larger than were those associated with test scores.

A limitation of the present investigation, in relation to this integration of the I/E, REM, and developmental equilibrium, is that German achievement and self-concepts were not collected in Years 5 through 9. Thus, the positive effects of Year 4 math grades on MSCs in Years 5 through 9 were

remarkably robust, as were the negative effects of Year 4 German grades on MSCs in Years 5 through 9. However, it was not possible to test the corresponding predictions about the effects of math and German grades on German ASCs in Years 5 through 9.

Importantly, integration of the I/E model and REM suggests a provocative new prediction that we were unable to test with the data available. The REM highlights the reciprocal effects of achievement and self-concept in matching domains, while the I/E model emphasizes effects of achievement on self-concept in contrasting domains that are negative. Integrating the two suggests that prior self-concept in one domain should have a negative effect on subsequent achievement in a contrasting domain. Although tests of this prediction must be left for future research (but see Möller, Retelsdorf, Köller, & Marsh, 2011), as it is not testable with the available data, this new prediction demonstrates the heuristic value of the integration of the different theoretical models (also see the online Supplemental Materials, Section 7).

Extending the BFLPE and Its Integration With the I/E Model, REM, and Developmental Equilibrium

Our study provides new perspectives on the potential limitations of previous BFLPE studies. These include the focus on explicit (rather than de facto) tracking, the inclusion of multiple contextual variables reflecting school-average achievement, and the juxtaposition of BFLPEs based on school-average achievement inferred from school grades with those inferred from standardized test scores. Of particular importance, our longitudinal analyses and our focus on developmental equilibrium have demonstrated the generalizability of BFLPEs over time (BFLPEs in Years 5 through 9) and over the different contextual variables used to represent school-average achievement.

The juxtaposition between these three contextual measures of school-average achievement is important in addressing a potential confounding of the temporal ordering of ASC and achievement in most BFLPE studies. In particular, because most BFLPE studies are based on a single wave of data, school-average achievement typically is inferred from test scores collected at the same time as the ASC measures. In our investigation, this was the case with BFLPEs based on school-average test scores from Year 5 (collected after students had already started secondary school). However, we showed that these potentially confounded effects on this contextual variable were consistent with

those for school-average achievement based on Year 4 school grades and school track, true pretreatment variables determined before students began their secondary schooling. This consistency was also evident in the substantial correlations among the three contextual variables (r s of .89 to .94), which allowed us to combine them into a single latent factor (i.e., the integrated ASC model). BFLPE estimates based on this latent factor were somewhat larger than were BFLPEs based on any of the measures considered separately. In summary, our study is apparently the first BFLPE study to use school grades prior to the start of secondary school to assess contextual effects, but also the first to demonstrate support for a latent school-average factor based on such apparently diverse measures of school-average achievement.

The integration of the BFLPE with developmental equilibrium also addresses a critical issue about whether the size of the BFLPE diminishes over time, remains stable, or actually becomes more negative as students progress through school. Previous research suggests that the BFLPE grows more negative over time, but this research is typically based on a limited time span or multiple, cross-sectional cohorts. In contrast, developmental equilibrium suggests that the BFLPE should remain consistent over time. Our longitudinal study, based on six waves of data, was uniquely suited to address this issue. In line with a developmental equilibrium perspective, the direction and even the sizes of the BFLPEs were reasonably consistent over Years 5 through 9. Although linear and quadratic effects were nonsignificant, a test of equality of the BFLPEs over time was rejected. In keeping with previous research suggesting that the BFLPE becomes more negative over time, the most negative BFLPE was for Year 9, the last year of compulsory education. However, the BFLPE at Year 9 was not significantly different from the average BFLPE for Years 5 through 8. Hence, there was no clear resolution as to whether the BFLPE remains stable (developmental equilibrium) or becomes increasingly negative over time (as suggested by previous research). However, it is apparent that the strength of the BFLPE does not diminish over time. In summary, the BFLPE is highly robust, with enduring negative effects across the first 5 years of secondary school.

The integration of the BFLPE model and the I/E model provides an interesting new prediction about the effects of school-average math and German school grades on MSC. At the level of the individual student in the multilevel model, support for the I/E model shows that the effects based on

math and German school grades on MSC go in opposite directions (positive for math grades and negative for German grades). Extending this I/E logic to the level of school-average achievement, there might also be counter- balancing effects of school-average math and German achievement on MSC (negative for school-average math achievement, positive for school-average German achievement). However, these two contextual variables reflect similar processes, in that math and German achievement are substantially correlated at the level of the individual student, and the track to which a student is assigned is based substantially on both math and German achievement. Thus, the school-average measures based on math and German school grades are so highly correlated ($r = .985$) that these contextual effects cannot be readily distinguished. However, as suggested by Marsh (1991), better support might be found in studies where selection into magnet schools is based on achievement in one narrowly defined academic domain (e.g., math, science, literature, sport, performing arts; see Marsh & Roche, 1996; Parker, Marsh, Lüdtke, & Trautwein, 2013; Trautwein, Gerlach, & Lüdtke, 2008) that is made highly salient to students, rather than a global measure that encompasses a diverse range of different domains. Hence, whereas here we found no support for this prediction based on the integration of the I/E and BFLPE perspectives, the rationale warrants consideration in different settings where school-average achievement in different academic domains is not so highly correlated.

Integrating ASC Models and Developmental Equilibrium into a Socio-Ecological Systems

Model

The integrated ASC model can also be analyzed in terms of a broad socioecological systems model (e.g., Bronfenbrenner, 1979). This paradigm shows not only how the integration works at different levels, but how it results in new predictions at different levels of the system. At the exosystem level, Germany's system provides a critical test case for self-concept research, evidenced by the amount and quality of research on the topic emerging from the country (e.g., Marsh, Köller, & Baumert, 2001; also see review by Marsh & Seaton, 2015) and by the fact that BFLPEs are largest in tracking countries like Germany (Nagengast & Marsh, 2012; Salchegger, 2016). The effect of tracking on children is mediated down to individuals through school selection at the microsystem level through the BFLPE, which is intensified in countries with highly stratified school systems. At the individual level the BFLPE has its influence directly on the external comparison aspect of the I/E

model. This in turn has an influence on the individual chronosphere level via the REM model, in which ASC but also achievement subsequently feedback up to microsystem, exosystem, and macrosystem (i.e., student performance and well-being ultimately are inputs into government decision processes about how to structure educational systems). Our article then explores how this developmental system as a whole operates and whether it is stable across a critical developmental period (developmental equilibrium) and thus largely immune to maturation effects.

Strengths, Limitations, Directions for Further Research, and Implications for Practice

The present investigation had a number of strengths that provide directions for future research, particularly research that seeks to integrate predictions and developmental perspectives based on the I/E, REM, and BFLPE models. Of particular importance were: an appropriate data set with multiple waves of data (preferably three or more), multiple content domains (typically math and verbal, but possibly more than two), and representative samples of students from a large number of different schools. Although the focus of this study was on developmental perspectives in relation to the integration of three theoretical models of self-concept formation, like Fraley et al. (2013) we suggest that this synergy of strong theoretical models, suitable longitudinal data, and appropriate statistical models, provides a more general framework in which to study patterns of associations across time that address critical issues in developmental science. Of course, this framework is flexible in relation to variations that might be useful in examining issues other than those addressed here. Thus, for example, it is possible to relax the equality constraints over time, so as to introduce more complex processes (e.g., so-called sleeper effects in which the effects increase over time). More generally, these conceptual frameworks and statistical models could also be useful for studying entirely different constructs and theoretical models.

Our integrated ASC model also provides an opportunity to consider new predictions that are not evident in any of the component models considered in isolation (for further discussion, see the online Supplemental Materials, Section 7). For example, how does the internal component of the I/E model operate within this system? The REM posits that ASC has reciprocal effects with achievement in matching areas, but the internal comparison process of the I/E model suggests that the effects of ASC might be negative for achievement in nonmatching areas (e.g., effect of MSC on verbal

achievement). The BFLPE posits that school- average achievement has a negative effect on ASC in the matching area, but the internal comparison process of the I/E model suggests that the effects of school-average achievement might be positive for achievement in nonmatching areas (e.g., effect of school- average verbal achievement on MSC).

In relation to potential weaknesses and directions for further research, our theoretical models posit causal effects. Although it is appropriate to make causal predictions, it is important to emphasize that our structural equation models do not conclusive fully test causality (see related discussion by Fraley et al., 2013). In the absence of random assignment with experimental manipulation, or even when there is random assignment, typically there are alternative explanations of the effects that may differ from implicit causal interpretations. Thus we use the term “effect” in its conventional statistical sense, as representing a relation that is not necessarily causal; we specifically avoid making the imputation that our effects are causal. Nevertheless, it is relevant to note that the design of our longitudinal study, with six waves of data, including a primary school measure of achievement, is stronger than most previous nonexperimental research. Particularly in relation to interpretation of the BFLPE, primary school grades and the tracking variable constitute true preintervention variables in relation to the move from untracked primary schools to highly tracked, ability-stratified high schools. This quasi-experimental design is apparently stronger than previous nonexperimental BFLPE research, and alternative designs that do not involve random assignment. Finally, we also note that the conceptual frameworks and statistical models developed here would also be useful in evaluating true intervention studies in which there is random assignment to conditions. Thus, for example, essentially the same model would be appropriate in a hypothetical true experimental study in which students were randomly assigned to students to schools differing in levels of academic achievement.

Here we used the manifest model of the BFLPE as described by Marsh, et al. (2009), where, even for the simplest contextual models, at least 50 and preferably as many as 100 schools are recommended. Where the number of schools is relatively small (less than 50, as in our study), they found that the more parsimonious manifest models are likely to be more accurate. Nevertheless, it would be desirable for future studies to include more schools than were considered here.

Our focus was on the BFLPE and ASC over this early to middle adolescent period. However, there is also a need to extend this research to include other developmental periods (e.g., early to middle childhood, where tests of developmental equilibrium might not be supported), to expand the tests to include data beyond those from secondary school, and to consider other outcomes, including long-term effects on academic achievement, aspirations, and educational attainment. Also, it would be interesting to see the inter- play of mechanisms underlying the three models of ASC over transitional periods other than the primary-to-secondary school transition considered here (e.g., secondary school to university, or from school to work). Finally, although some specific features of the German school system (particularly in relation to tracking) lent strengths to the present investigation, there is also a need to test the generalizability of the results in other countries and different school systems, and to test the extent to which results generalize across individual student and school-level characteristics within each study.

In respect of the nature of school grades, and of grading on a curve, the results provide an important demonstration that school grades can, in some circumstances, provide a common metric across different teachers and schools (see further discussion in the online Supplemental Materials, Section 1). However, our results are highly dependent on circumstances that, at least in part, are specific to the German school system. Hence, further research is needed to test the generalizability of these results and to improve the usefulness of school grades as a measure of achievement that is generalizable across teachers, school subjects, and schools.

In conclusion, in a rapidly changing world, the development of positive ASCs is important. Thus, for example, Marsh and Yeung (1997) demonstrated that ASC predicted subsequent coursework selection better than did corresponding measures of achievement, while Marsh and O'Mara (2008) showed that ASC formed in high school contributed to the prediction of long-term educational attainment 8 years later, beyond the effects of school grades, standardized achievement tests, IQ, and socioeconomic status. However, despite the tremendous growth and sophistication of ASC research in the last 30 years, major theoretical models (REM, I/E, and BFLPE) have tended to develop in isolation of each other, due in part to the methodological design complications associated with each.

Here we derived an integrative set of theoretical hypotheses that spans all three models, and offered new developmental perspectives in relation to tests of developmental equilibrium.

From a developmental perspective, we have expanded the theoretical and statistical rationale for tests of developmental equilibrium, given that our longitudinal data cover the potentially turbulent early to middle adolescent period. This perspective on the consistency of effects from one wave to the next is different from the typical developmental focus on the latent mean trajectories of a given construct in a period of developmental significance. Unlike many developmental studies, our focus was on developmental consistency of effects over time, rather than on developmental differences. More specifically, we found support for developmental equilibrium in terms of the invariance of effects across five waves of data, based on the assumption that the self-system had attained a developmental balance in relation to predictions from each of our theoretical models of ASC formation. Although developmental equilibrium is a powerful lens to bring a developmental perspective to each of these theoretical models, it is important to emphasize that these models do not per se depend on developmental equilibrium: the consistency of effects over a developmental period of interest. Developmental equilibrium does, however, provide an important test of whether the dynamics underlying the formation of ASC in these models have reached a state of balance over the developmental period under consideration.

In extending tests of developmental equilibrium, we offer new developmental perspectives on each of the three ASC models, including the need for longitudinal data based on more than just 2 or 3 waves, and for stronger tests of the statistical assumptions underlying the models. Indeed, we suspect that our finding of significant effects associated with lag-2, lag-3, and even lag-4 autocorrelation effects would be likely in many developmental studies if this was tested formally on the basis of a sufficient number of waves. From a statistical and design perspective, this finding is important, because failure to consider these higher order lags (because, e.g., only two waves of data were collected, or the lags were simply ignored) is likely to positively bias results, unless there is strong evidence that they are insignificant. Such results might be merely a statistical issue, in that the results of two measures of the same construct are likely to better predict a third measure than either one considered separately. However, although this is beyond the scope of the present investigation, there

might also be substantively important implications of the higher order lagged effects. For example, materials taught and tested in Year 5 might lead to materials being covered in Year 7 but not tested in Year 6, so that mastery of materials in Year 5 contributes to prediction of achievement in Year 7 beyond what can be explained in terms of achievement in Year 6. More research is needed to disentangle statistical from substantive issues in the interpretation of lag-2, lag-3, and even lag-4 autocorrelation effects. Nevertheless, the default assumption should be that these higher order lagged effects do exist, in the absence of empirical tests showing that they are nonsignificant.

From the perspective of educational practice, we found that the feedback students received, in the form of teacher-assigned grades, reciprocally influenced the development of their ASCs over 5 years. However, grading that uses normative standards, such as grading on the curve, inevitably implies that some students can experience success, whereas others must fail; accordingly, the findings suggest that normative grading should be replaced by absolute or individual standards wherever possible, to promote students' ASCs. Indeed, support for the REM suggests why the job of the classroom teacher is so difficult; they need to teach academic skills, but also to reinforce positive self-beliefs and link the two in a way that is consistent with their reciprocal relations, in which each contributes to the other. Finally, the effects of school- average achievement (defined by test scores or grades) and school track on ASC were consistently negative over the secondary school years. Accordingly, parents and teachers are well advised to consider ASC implications when reaching decisions about how best to select schools and classes for their children.

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Table 1

Integrated ASC Model: Path Coefficients Leading From Predictor Variables in Years 4–8 to Math Outcomes (School Grades, Self-Concept, Test Scores) in Years 5–9

Prediction Of Math Self			Prediction Of Math Grade			Prediction Of Math Test		
Predictors	Est	SE	Predictors	Est	SE	Predictors	Est	SE
MSelf5			MGrd5			MTest5		
MGrd4	.49	.04	MGrd4	.42	.03	MGrd4	.59	.03
GGrd4	-.26	.04	GGrd4	.01	.03	GGrd4	.09	.03
MSelf6			MGrd6			MTest6		
MSelf5	.45	.01	MGrd5	.47	.02	MTest5	.48	.02
MTest5	.11	.02	MTest5	.17	.02	MSelf5	.04	.01
MGrd5	.14	.02	MSelf5	.07	.01	MGrd5	.04	.01
MGrd4	.18	.04	MGrd4	.13	.03	MGrd4	.25	.03
GGrd4	-.20	.04	GGrd4	-.07	.02	GGrd4	.13	.03
MSelf7			MGrd7			MTest7		
MSelf6	.45	.01	MGrd6	.47	.02	MTest6	.48	.02
MTest6	.11	.02	MTest6	.17	.02	MSelf6	.04	.01
MGrd6	.14	.02	MSelf6	.07	.01	MGrd6	.04	.01
MGrd4	.03	.04	MGrd4	.03	.03	MGrd4	.13	.03
GGrd4	-.12	.03	GGrd4	-.02	.03	GGrd4	.06	.03
MSelf8			MGrd8			MTest8		
MSelf7	.45	.01	MGrd7	.47	.02	MTest7	.48	.02
MTest7	.11	.02	MTest7	.17	.02	MSelf7	.04	.01
MGrd7	.14	.02	MSelf7	.07	.01	MGrd7	.04	.01
MGrd4	.03	.04	MGrd4	-.04	.03	MGrd4	.11	.02
GGrd4	-.08	.04	GGrd4	-.06	.03	GGrd4	.09	.02
MSelf9			MGrd9			MTest9		
MSelf8	.45	.01	MGrd8	.47	.02	MTest8	.48	.02
MTest8	.11	.02	MTest8	.17	.02	MSelf8	.04	.01
MGrd8	.14	.02	MSelf8	.07	.01	MGrd8	.04	.01
MGrd4	.03	.04	MGrd4	-.04	.03	MGrd4	.08	.02
GGrd4	-.03	.04	GGrd4	-.02	.03	GGrd4	.05	.02
BFLPE								
Schl-Ach5	-.25	.08						
Schl-Ach	.03	.12						
Schl-Ach	.03	.09						
Schl-Ach	-.01	.07						
Schl-Ach	-.17	.07						

Note. Mgrad = Math School grades (Years 4–9), MSelf = Math self-concept (Years 5–9), MTest5 = math test scores (Years 5–9), Dgrad = German (Deutsch), School grades (Year 4 only), pred = predictor variables, I/E = internal/external, DevEq = Developmental Equilibrium; Coefficients more than 1.96 times its standard error (values in parentheses) are statistically significant at a nominal $p < .05$. Consistently with support for developmental equilibrium, lagged paths are constrained to be invariant across the Years 5–9. For example, the lag-1 path $Mtest_{Year5} \rightarrow MSELF_{Year6} = .447$ is equal to the corresponding lag-1 path $Mtest_{Year6} \rightarrow MSELF_{Year7} = .447$). The results from this model are used to test predictions in relation to developmental equilibrium (DevEq), the internal/external frame of reference model (I/E), the reciprocal effects model (REM), and the big-fish-little-pond effect (BFLPE). Coefficients in bold are statistically significant $p < .05$.

Table 2

Tests of the Internal/External Frame of Reference Model (Hypothesis 2^a: Effects of Primary School (Year 4) Math and German School Grades on Math Self-Concepts, Grades, and Test Scores in Secondary School Years 5–9 (Internal/External Frame of Reference Model, Hypothesis 2)

Year	Predictor		Outcome Prediction of:					
			Math Self		Math Grade		Math Test	
			Est	SE	Est	SE	Est	SE
Year 5	Total	MGrd4	.49	.04	.42	.03	.59	.03
		GGrd4	-.26	.04	.01	.03	.09	.03
	Direct	MGrd4	.49	.04	.42	.03	.59	.03
		GGrd4	-.26	.04	.01	.03	.09	.03
Year 6	Total	MGrd4	.54	.05	.46	.03	.57	.03
		GGrd4	-.29	.05	-.07	.03	.16	.03
	Direct	MGrd4	.18	.04	.13	.03	.25	.03
		GGrd4	-.20	.04	-.07	.02	.13	.03
Year 7	Total	MGrd4	.48	.04	.38	.04	.56	.04
		GGrd4	-.28	.04	-.04	.04	.15	.04
	Direct	MGrd4	.03	.04	.03	.03	.13	.03
		GGrd4	-.12	.03	-.02	.03	.06	.03
Year 8	Total	MGrd4	.48	.05	.34	.03	.58	.03
		GGrd4	-.27	.04	-.09	.03	.19	.03
	Direct	MGrd4	.03	.04	-.04	.03	.11	.02
		GGrd4	-.08	.04	-.06	.03	.09	.02
Year 9	Total	MGrd4	.49	.04	.34	.03	.58	.03
		GGrd4	-.25	.05	-.06	.03	.18	.03
	Direct	MGrd4	.03	.04	-.04	.03	.08	.02
		GGrd4	-.03	.04	-.02	.03	.05	.02

Note. Effects (standard errors in parentheses) of German and math school grades from primary school (Year 4) on secondary school outcomes in Years 5–9 (math self-concept, math school grades, and math test scores). Total effects include both direct and indirect effects. Thus, for example, the total effects of Year 4 math grades on Math grades in Years 5–9 are consistently substantial (.459 to .420), but direct effects are only significant for Years 5 and 6; most of the effects of Year 4 Math school grades on Math grades in Years 7–9 are mediated through math grades in Years 5 and 6 (also see Table 1, where the direct effects associated with Hypothesis 2 are presented, shaded in light gray; also see Supplemental Materials, Section 4 for further discussion). Coefficients in bold are statistically significant $p < .05$.

^a See Figure 1 and Tables 1 and 2

Table 3

Tests of the Reciprocal Effects Model (Hypothesis 3) Based on Model^a: Lag-1 Paths From Each Predictor Variable in one Year to Each Outcome in the Next Year for Math Self-Concepts, Grades, and Test Scores in Secondary School Years 5–9

Predictors	Outcome Prediction of:					
	Math Self		Math Grade		Math Test	
	Est	SE	Est	SE	Est	SE
Integrated ASC Model (Grades & Tests)						
Math Self-concept	.45	.01	.07	.01	.04	.01
Math Grades	.14	.02	.47	.02	.04	.01
Math Tests	.11	.02	.17	.02	.48	.02
Predictor Grades Only						
Math Self-concept	.48	.01	.10	.01		
Math Grades	.16	.01	.51	.02		
Predictor Test Only						
Math Self-concept	.52	.01			.05	.01
Math Tests	.13	.02			.62	.02

Note. Estimates (standard errors in parentheses) for the Integrated ASC Model come from Table 1 (Figure 1). For the reciprocal effects model, critical paths (shaded in gray) in relation to a priori predictions are the cross-paths leading from each predictor variable in one wave to a different outcome variable in the next wave (e.g., $Mtest_{Year5} \rightarrow MSELF_{Year6}$). Horizontal paths are paths from each variable to the same variable in a subsequent wave (e.g., $Mtest_{Year5} \rightarrow MSC_{Year6}$). Consistently with support for developmental equilibrium in the Integrated ASC Model, lag-1 paths are constrained to be invariant across the Years 5–9 (i.e., $Mtest_{Year5} \rightarrow MSC_{Year6} = Mtest_{Year6} \rightarrow MSC_{Year7}$). The results for the Integrated ASC Model shown here are the same as in Table 1, where the full set of paths is presented (also see Supplemental Materials, Section 5 for further discussion) and include both math grades and tests across the five year groups. In variations to the Integrated ASC Model specific to the reciprocal effects model, we tested separate for math grades and standardized tests. Coefficients in bold are statistically significant $p < .05$.

Table 4

Big-Fish-Little Pond Effect (BFLPE): Effects of School-Average Variables on Math Self-Concept in Years 5–9 (Hypothesis 4)

Dependent	Common Model		Model A1		Model A2		Model A3		Model B1	
	Latent Factor		School Average		School		School Average		School Average	
	(A1+A2+A3)		Math Grades		Track		Math Test		German Grades	
	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
MSC-Year5 Total	-.25	.08	-.18	.06	-.16	.05	-.23	.07	-.20	.06
Direct	-.25	.08	-.18	.06	-.16	.05	-.23	.07	-.20	.06
MSC-Year6 Total	-.26	.08	-.19	.06	-.17	.05	-.23	.07	-.20	.06
Direct	.03	.12	.02	.08	.01	.07	.04	.10	.04	.10
MSC-Year7 Total	-.18	.08	-.13	.06	-.10	.05	-.18	.07	-.12	.06
Direct	.03	.09	.03	.06	.04	.05	-.02	.08	.05	.07
MSC-Year8 Total	-.13	.06	-.10	.05	-.07	.04	-.14	.06	-.10	.05
Direct	-.01	.07	.00	.05	.00	.04	.00	.05	-.02	.05
MSC-Year9 total	-.31	.09	-.22	.07	-.19	.06	-.28	.08	-.22	.07
Direct	-.17	.07	-.11	.05	-.11	.04	-.14	.06	-.11	.05
Mean Total Effect	-.23		-.16		-.14		-.21		-.17	

Note. MSC = math self-concept; Year 5–Year 9 = first five years in secondary school. Estimates (standard errors in parentheses) for the direct paths from school-average achievement come from the Integrated ASC Model (see level 2 estimates in Table 1 and Figure 1; also see structure of individual student level in the Integrated ASC Model) and the corresponding total effects (shaded in gray). In the Integrated ASC Model, school-average achievement represented by one latent variable (based on school-average values for math grades, school track, and test scores). In additional models specific to tests of the BFLPE, separate analyses were done for each of these three measures of school-average math achievement: School average math grades (Model A1, based on Year 4, the last year of primary school); school track (Model A2: high, medium, low track determined prior to the start of secondary school); and school-average test scores (Model A3, based on test scores from Year 5, the first year of secondary school). Model B1 tests the effects of school-average German grades. Coefficients in bold are statistically significant $p < .05$.

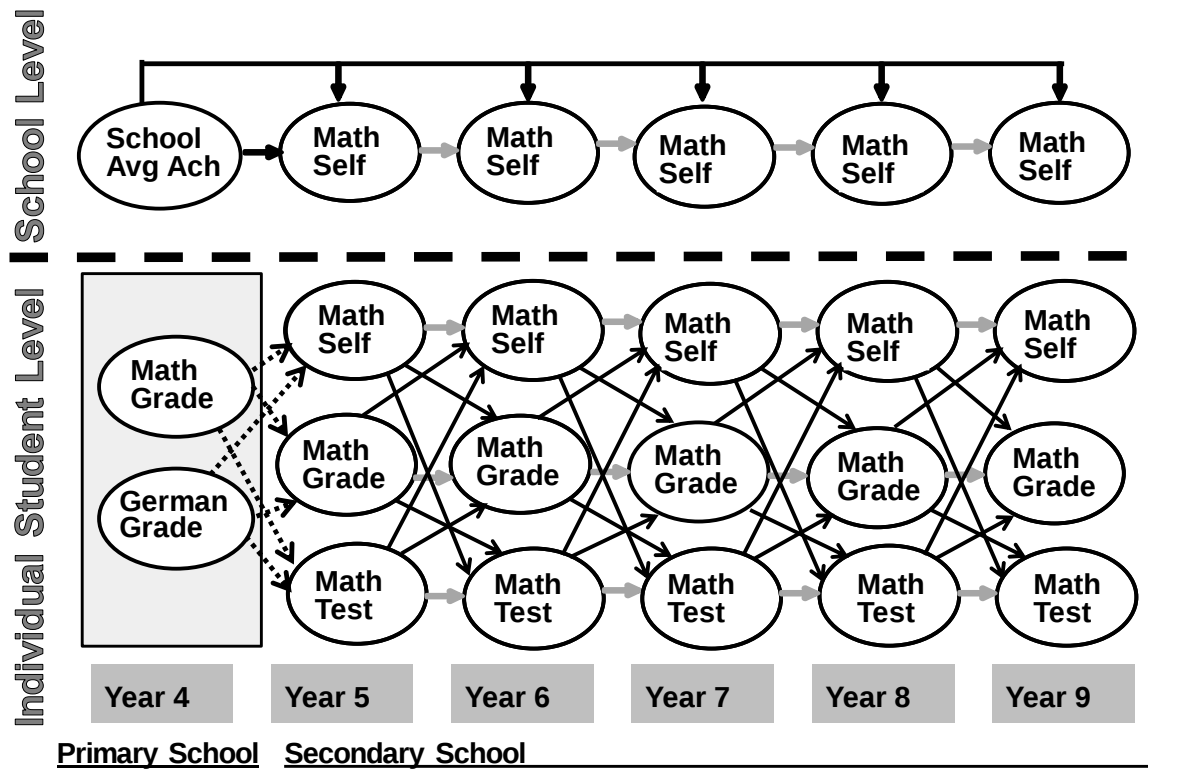


Figure 1. Integrated Academic Self-Concept Model. This single conceptual model (and associated statistical model in Table 1) provides tests of all three theoretical models of academic self-concept (ASC) and developmental equilibrium. The paths from math and German grades in Year 4 to MSC in Years 5–9 provide tests of the internal/external frame of reference model. The paths relating math achievement (test scores and grades) and self-concept in Years 5–8 to these measures in subsequent years provide tests of the reciprocal effects model. At the school level, the paths from school-average achievement to MSC provide tests of the big-fish-little-pond effect. The consistency of the paths over time provides tests of developmental equilibrium. For the purposes of illustration, only lag-1 paths are shown (effects of each variable on variables in the immediately subsequent wave). However, in the final a priori model (the Integrated ASC Model, Table 1; also see Supplemental Materials, Section 3) are shown:

- (i) Paths from both math and German grades in Year 4 to all Years 5–9 outcomes (the dashed lines from Year 4 school grades to Year 5, but also paths for Year 4 school grades to outcomes in Years 6–9);
- (ii) All lag-1 to lag-4 autocorrelation (horizontal) test-retest paths relating all Years 5–9 variables in each Year to the same variable in all subsequent Years (the solid horizontal lines from each variable in Years 5–8 to the same variable in the next Year, lag-1 paths, but also paths from each variable to the same variable in all subsequent Years—lags 2–4). These paths are constrained to be invariant across Years (e.g., lag-1 paths from test scores in Year 5 to test scores in Year 6 are the same as the lag-1 path from test scores Year 8 to test scores in Year 9).
- (iii) All lag-1 and lag-2 cross-paths relating all Years 5–9 variables in each Year to each of the different variables in the next Year (only lag-1 paths are shown). These paths were constrained to be invariant across Years (e.g., lag-1 paths from test scores_{Year5} to MSC in Year 6 were the same as the lag-1 path from test scores in Year 8 to MSC in Year 9) and
- (iv) Covariances between all variables measured within the same wave (e.g., math and German grades at Year 4; MSC, test scores, and grades at Year 5).

Support for developmental equilibrium is based on goodness of fit tests (presented in greater detail in the Supplemental Materials, Section 3) that provide support for this a priori prediction, and a statistical basis for constraining paths to be invariant across Years. Parameter estimates (Table 1) from this one multilevel, longitudinal path model are used to test the internal/external frame of reference model, the reciprocal effects model and the big-fish-little-pond effect, in which school-average achievement is based on various combinations of Year 4 school grades, school track, and Year 5 test scores. The Mplus syntax and output showing the full set of lagged paths are presented in the Supplemental Materials, Section 8.

SUPPLEMENTAL MATERIALS

Section 1: An Extended Discussion of the Theoretical Basis of Developmental Equilibrium

Section 2: Presentation of Descriptive Statistical and Correlations Among the Constructs

- Primary-school math grades
- Primary-school German grades
- Relations with math self-concepts (MSC)
- Developmental trajectories
- Grading on a curve
- Supplemental Table 1: Correlations among student-level variables

Section 3: Extended Discussion of Preliminary Analyses: Selection of the Most Appropriate Baseline Model

- Goodness of fit
- Pattern and invariance of path coefficients
- Support for developmental equilibrium
- Supplemental Table 2: Goodness of fit for alternative REM path models of pretest (Year 4) variables, and the autocorrelation and cross paths (following from Figure 1)

Section 4: The I/E model (Hypothesis 1)—Extended Analyses of the Effects of Year 4 Variables with Controls for Intervening Variables (Following from Table 3 in the Main Text)

Section 5: The Reciprocal Effects Model (REM, Hypothesis 2)—Temporal Ordering of School Grades, Test Scores and Self-Concept (Hypothesis 3): Selected Output From the Extended Analysis of Results Reported in Table 4 of Main Text

Section 6: BFLPEs: The Negative Effects of School-Average ACH (Hypothesis 4)—Extended

- Extended discussion: Rationale for tests of the BFLPE
- Juxtaposition between reflected glory (assimilation) and social comparison (contrast) effects

Section 7: Eighteen New Theoretical Predictions Derived From the Integration of the Three Theoretical Models of ASC Formation and Developmental Equilibrium

Section 8: Mplus Syntax Used to Test the Integrated ASC Model (see Section 2)

- Mplus syntax
- Mplus results (an extended version of parameter estimates presented in Table 1 of the main text)

Supplemental Materials Section 1: An Extended Discussion of the Theoretical Basis of

Developmental Equilibrium

In research with longitudinal data, a number of developmental questions can be considered, relative to consistency over time and change. However, we note that due in part to the historical focus on hypothesis testing in relation to a null hypothesis, in developmental studies there is a traditional emphasis on change rather than consistency over time. Nevertheless, the null hypothesis approach can be misleading, in that even trivial amounts of change can be statistically significant when based on a sufficiently large *N*. Hyde (2005) for example, notes that in respect of gender differences/similarities, a focus on small but statistically significant gender differences tends to ignore the strong support for gender similarities, in a way that can do much harm and lead to counter-productive policies. Consequently, we take a model-based approach based on goodness of fit, using criteria that are independent of sample size, comparing more parsimonious models that impose consistency over time through invariance constraints with models that do not assume consistency of relations over time. Thus we propose a model of consistency over time as a research hypothesis, test the hypotheses empirically, and interpret the results in terms of relative degrees of consistency over time and change.

Questions of consistency over time and change in longitudinal data fall into two main perspectives. First, longitudinal research can consider trajectories in the means of a given construct related to a period of developmental significance. For example, does self-concept decline over adolescence? Second, the focus of our study, researchers can consider consistency over time/change in relations between constructs during a period of developmental significance. Thus, for example, Davis-Kean et al. (2008; also see Davis-Kean, Jagen & Collins, 2009) reported that the relation between ASC and achievement changed with age for young children, but became relatively stable from the age of about 12. This suggests that this relation is stable during the early-to-middle adolescent period that is the focus of our study. Importantly, these two approaches—consistency over time/change of means and consistency over time/change of relations—are separate: patterns of relations between variables can remain stable even when there are systematic changes in mean levels. Although we explore both perspectives, our major focus is on the second: tests of the consistency over time of relations between

ASC and achievement in relation to predictions from three theoretical models, over the potentially turbulent six-year period of early-to-middle adolescence.

In each of the different perspectives on equilibrium (see discussion in main text under “Integrating Developmental Equilibrium into the Integrated ASC Model”), the critical issue is of balance, posited to be a psychologically desirable state, and indicating consistency over time. Here we evaluate support for developmental equilibrium through tests of the consistency of relations among critical variables over early-to-middle adolescence—whether the self-system is in a state of balance in relation to consistency over time of relations during this period. Thus, for example, in related applications of this concept of developmental equilibrium, Marshall et al. (2015) showed that a system of reciprocal effects between self-concept and social support had attained equilibrium by junior high school; Marsh, Pekrun, Lichtenfeld, et al. (2016) showed that double-edged effects of effort—positive for achievement but negative for self-concept—had attained a state of equilibrium over the adolescent period; and Marsh, Craven, et. al. (2016) showed that the pattern of reciprocal effects of aggression, victimization, and depression had achieved equilibrium over secondary school years. In related work, Davis-Kean, Jagen & Collins (2009; also see Davis-Kean, et al., 2008) reported that ASC and achievement were negligibly related for young children, but became stably related by about the age of 12; this suggests that this relation had attained a state of equilibrium by early-to-middle adolescence.

As noted in the main paper, while “equilibrium” is often used metaphorically, we operationalized it by integrating it with formal statistical models of longitudinal invariance. Thus, for example, tests of the REM model of relations between achievement and ASC typically are based on two measurement waves, to test the temporal ordering (Huang, 2011; Valentine et al., 2004), but at least three waves—and preferably more—are required to test developmental equilibrium assumptions that the pattern of reciprocal effects of one variable on another across any two waves is consistent over multiple waves. Statistical models of developmental equilibrium (invariance of effects of one variable on another over multiple waves) test whether the developmental state is in balance over the period under consideration. Furthermore, support for tests of developmental equilibrium also facilitates interpretation of the results, providing a more parsimonious model, and resulting in statistically stronger tests of a priori

predictions (also see Little et al., 2007, for more general discussion of stationarity assumptions in cross-lag panel studies).

We also note that our notion of developmental equilibrium closely resembles Fraley, Roisman, and Haltigan's (2013) "Legacy of Early Experiences in Development" which they present an important, ongoing debate in developmental science—whether early experience in social and cognitive development has enduring long-term effects. Specifically, they argue: "By studying the pattern of associations across time, it should be possible to gain greater insight into the legacy of early experiences" (p. 113). Whereas Fraley et al. focused on the effects of maternal caregiving experiences in the first three years of life, their conceptual framework is similar to the model we used to test for developmental equilibrium. Indeed, their paradigmatic models (Figure 4 in their article) closely resemble our Integrated ASC Model (see earlier discussion of our Figure 1).

Similarly to our evaluation of primary school grades and school-average ability, they proposed models of the longitudinal effects of a particular event in time (the first model in their Figure 4). Their emphasis, like ours, was on the direct and indirect effects of a variable over time. However, as in our evaluation of the REM, they also proposed cross-lagged panel models of the same variables measured on multiple occasions over time (their second model their Figure 2). As in the present investigation, Fraley et al. proposed models with paths greater than lag-1 (i.e., paths relating variables separated by more than one data wave; the third model in their Figure 4).

Like us, they contend that the study of patterns of associations over time is one of the central issues in developmental science. Indeed, our a priori hypothesis of developmental equilibrium can be seen as a special case of a more general model, in which selected effects are consistent over time—a possibility that they introduced by testing the equality of parameter estimates across multiple waves of data. Thus, for Fraley et al., consideration of these developmental issues requires more than two waves of data and preferably many, in which the same constructs are studied—ideally, covering an important developmental period. Further, their study, like ours, integrates multiple models into a single theoretical and statistical framework (the fourth model in their Figure 4).

Here we formally test developmental equilibrium as the invariance of effects across five waves of data, on the basis of the assumption that the self-system has attained a developmental balance in

respect of predictions from the three ASC models. To test these a priori hypotheses, we use a uniquely appropriate data set (a representative sample of 3,370 students from 42 schools measured over a six-year period of early-to-middle adolescence). Although the tests of developmental trends in support for each of these models separately have important theoretical and substantive implications, our formal tests of developmental equilibrium across all three models provide stronger tests of developmental trends and consistencies. Indeed, there are theoretical, developmental, and substantive implications: the question whether the effect sizes of critical components in each of these models of ASC formation vary developmentally (Eccles, 2009; Marsh, 2007; Marsh & O'Mara, 2008; Marsh, Seaton, et al., 2008; Murayama et al., 2013); the relative sizes of paths leading from achievement to ASC paths and ASC to achievement in the REM; the size of the BFLPE; and the strength of the internal comparison process in the I/E model.

Supplemental Materials Section 2:

Presentation of Descriptive Statistical and Correlations Among the Constructs

Primary-school math grades. Correlations between primary-school (Year 4) math grades and math test scores in secondary school (Years 5–9) are substantial and remarkably consistent across the five years ($r_s = .65$ to $.70$; Table 1). These correlations are consistently higher than correlations relating math school grades in Years 5–9 to math test scores in Years 5–9 ($r_s = .28$ to $.53$). These results also suggest that school grades in untracked primary schools are more like test scores, in that they reflect a more common underlying metric continuum than do grades in Years 5–9 in the highly tracked secondary schools. These results have potentially important implications for understanding the grading on a curve phenomenon, as well as our subsequent use of school-average achievement based on these Year 4 math grades.

Primary-school German grades. Primary school German grades are substantially correlated with math test scores in Years 5–9 ($r_s = .48$ to $.57$), consistently less correlated with math school grades in Years 5–9 ($r_s = .12$ to $.28$), and nearly uncorrelated with MSCs in Years 5–9 ($r_s = -.03$ to $-.07$). Again, these results suggest that primary school grades are behaving more like test scores than are school grades in Years 5–9. The near-zero correlations of German school grades with MSCs reflect the extreme domain specificity of ASCs, the focus of subsequent tests of the I/E frame of reference effect in this study.

Relations with math self-concepts (MSC). Finally, in keeping with a substantial amount of previous research, correlations between MSCs and school grades in the same year ($r_s = .42$ to $.62$; Table 1) are consistently higher than the corresponding correlations between MSCs and test scores ($r_s = .30$ to $.34$; Table 1). This finding is also the focus of subsequent tests of the REM relating test scores, school grades and MSC.

Developmental trajectories. Although this is not a primary focus of the present investigation, it is of interest to consider the developmental trajectories of our key constructs, how our background variables (IQ, gender, SES) relate to our key constructs, and how consistent these effects are across this potentially volatile developmental period. The steady decline in MSC across Years 5–9 is

consistent with a considerable body of research (e.g., Eccles, 2009; Jacobs, et. al., 2002; Marsh, 2007). Gender differences in favor of males are evident, particularly for MSC and math test scores, whereas gender differences in school grades are small. These gender differences are relatively stable over adolescent years. SES is positively related to grades and particularly to test scores, but only weakly related to MSC. Again, these effects are reasonably consistent over the adolescent years. IQ is more strongly related to test scores than to school grades, and less positively related to MSCs (see further discussion in these Supplemental Materials, Section 6, and in relation to discussion of the REM).

Grading on a Curve. We began by evaluating correlations among the variables across the 6 waves of data, with a particular focus on school grades from the final of primary school, Year 4. Because these grades were based on non-selective schools, the typical “grading on a curve” effects were substantially reduced, compared to those in the highly tracked secondary schools. Furthermore, these Year 4 grades were very salient to students and were important in determining the school tracks to which students subsequently would be assigned in Year 5. In line with this rationale, correlations between Year 4 math grades and math tests in the next five years were substantial and remarkably consistent over this period ($r_s = .65$ to $.70$; Table 1). Even more remarkable, perhaps, was the observation that Year 4 math grades were more highly correlated with math test scores in the next five years than were school grades from the same year as the math test. These results suggest that when students are in relatively heterogeneous groupings, the school grades provide a valuable indicator of achievement, in relation to a metric that is relatively common across schools. In this respect, Year 4 school grades behave more like standardized tests than do school grades in Years 5–9. However, in addition to the relatively pure measures of achievement provided by standardized tests, school grades also reflect motivational and psychological properties that influence classroom performance beyond those reflected by test scores. Indeed, this is why school grades are consistently more highly correlated with MSCs than are math test scores (Marsh, 2007; Marsh, Kuyper, Seaton et al., 2014). In summary, these results provide important insights into the grading on a curve phenomenon, which has been the focus of much ASC research, but also for policy-practice in relation to the interpretation of school grades and, perhaps, allocation of students to different achievement tracks in secondary school.

Supplemental Materials Table 1

Correlations Among Student-Level Variables

Means 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Self-Concept

1 ASC5	1																
2 ASC6	.596	1															
3 ASC7	.503	.624	1														
4 ASC8	.482	.549	.681	1													
5 ASC9	.458	.504	.618	.708	1												

Test Scores

6 MTSTN5	.320	.284	.256	.269	.234	1											
7 MTSTN6	.283	.297	.279	.283	.244	.777	1										
8 MTSTN7	.259	.287	.311	.318	.284	.735	.796	1									
9 MTSTN8	.270	.292	.306	.341	.303	.740	.815	.835	1								
10 MTSTN9	.246	.262	.264	.306	.306	.716	.772	.796	.862	1							

Math Grades

11 MGRD5	.420	.408	.346	.340	.357	.528	.508	.508	.498	.498	1						
12 MGRD6	.370	.518	.392	.394	.410	.475	.476	.488	.467	.446	.676	1					
13 MGRD7	.287	.359	.533	.463	.453	.375	.423	.445	.438	.425	.534	.590	1				
14 MGRD8	.299	.315	.423	.586	.527	.280	.308	.383	.378	.352	.475	.520	.631	1			
15 MGRD9	.272	.337	.392	.486	.621	.304	.321	.386	.416	.396	.470	.547	.612	.677	1		

Year 4 Grades

16 MGRD4	.209	.193	.179	.200	.180	.646	.671	.660	.698	.690	.428	.400	.335	.263	.264	1	
17 1DGRD4	-.053	-.069	-.061	-.025	-.039	.476	.532	.517	.565	.554	.284	.225	.195	.124	.141	.654	1

Background Variables

18 Male	.246	.210	.228	.213	.193	.116	.078	.033	.066	.071	.020	.022	.034	.014	-.022	.047	-.182
19 IQ	.146	.107	.136	.147	.146	.589	.613	.593	.607	.587	.390	.331	.277	.219	.241	.526	.485
20 SES	.065	.040	.022	.052	.040	.228	.261	.238	.272	.280	.150	.118	.115	.079	.075	.227	.269
Means	.000	-.189	-.463	-.464	-.523	.000	.000	.000	.000	.000	.000	-.048	-.261	-.203	-.232	.000	.000

Note. Yr5–Yr9 = (Years 5–9, the first five years of secondary school); MSC = math self-concept; Mtest = math standardized test; Mgrade = teacher-assigned mark; Math and German-Yr4 refer to school grades from Year 4 (last year of primary school prior to start of high school).

Supplemental Materials Section 3:

Extended Discussion of Preliminary Analyses: Selection of the Most Appropriate Baseline Model

Our main substantive interest was in the effects of the two Year 4 variables (math and German grades) and those of math grades, math tests and MSC on the same variable in the next wave (see Hypotheses 1–3), hereafter referred to as “lag-1” paths (see Figure 1). However, also included in the a priori path model were paths leading from the same variable collected in earlier data waves (higher order paths). Thus, for example, MSC in Year 9 was predicted by math self-concept, math test scores, and math grades from Year 8 (lag-1 variables), but also by math self-concepts from Waves 1–4 (lag 2–5) variables. The model is conservative in that it shows the effects of non-matching variables (e.g., the effects of math grades on math self-concept, controlling for prior math grades and test scores), particularly compared to studies that include only two or perhaps three waves of data. Although the a priori model considered here includes these test-retest autocorrelation paths from all waves, models positing only lag-1 paths were also evaluated, to determine whether support for a priori hypotheses depends on this methodological feature. In this section we present a summary of the preliminary analyses that led to the selection of the most appropriate latent variable (CFA and SEM) models used to test a priori hypotheses, starting with a discussion of goodness of fit.

On the basis of these preliminary analyses, the final model used here (see Figure 1) has the following features: (a) Paths from both math and German grades in Year 4 to all Years 5–9 outcomes (the dashed lines from Year 4 school grades to Year 5 outcomes shown in Figure 1, but also paths for Year 4 school grades to outcomes in Years 6–9). (b) All lag-1 to lag-4 autocorrelation (horizontal) paths relating all Years 5–9 variables in each wave to the same variable in all subsequent waves (the solid horizontal lines from each variable in Years 5–8 to the same variable in the next wave, lag-1 paths, in Figure 1, but also paths from each variable to the same variable in all subsequent waves—lags 2–4). These paths are constrained to be invariant across waves (e.g., lag-1 paths from test scores_{Year5} to test scores_{Year6} are the same as the lag-1 path from test scores_{Year8} to test scores_{Year9}). (c) All lag-1 cross-paths related all Years 5–9 variables in each wave to each of the different variables in the next wave (as in Figure 1, no cross-paths were included for lags 2–4). These lag-1 paths were

constrained to be invariant across waves (e.g., lag-1 paths from test scores_{Year5} to MSC_{Year6} were the same as the lag-1 path from test scores_{Year8} to MSC_{Year9}). (d) Support for developmental equilibrium is based on goodness of fit tests (see section entitled “Support for developmental equilibrium”) that provide support for this a priori prediction and a statistical basis for constraining paths to be invariant across waves.

Goodness of Fit

Generally, given the known sensitivity of the chi-square test to sample size, to minor deviations from multivariate normality, and to minor misspecifications, applied SEM research focuses on indices that are relatively sample-size independent (Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004; Marsh, Hau, & Grayson 2005), such as the Root Mean Square Error of Approximation (RMSEA), the Tucker-Lewis Index (TLI), and the Comparative Fit Index (CFI). Population values of TLI and CFI vary along a 0-to-1 continuum, in which values greater than .90 and .95 typically reflect acceptable and excellent fits to the data, respectively. Values smaller than .08 and .06 for the RMSEA support acceptable and good model fits, respectively.

The chi-square difference test can be used to compare two nested models, but this approach suffers from even more problems than does the chi-square test for single models—problems that led to the development of other fit indices (see Marsh, Hau & Grayson, 2005). Cheung and Rensvold (2002) and Chen (2007) suggested that if the decrease in fit for the more parsimonious model is less than .01 for incremental fit indices such as the CFI, there is reasonable support for the more parsimonious model. For indices that incorporate a penalty for lack of parsimony, such as the RMSEA and the TLI, it is also possible for a more restrictive model to result in a better fit than would a less restrictive model. However, it is emphasized that these cut-off values constitute rough guidelines only, rather than “golden rules” (Marsh, Hau, & Wen, 2004).

Pattern and Invariance of Path Coefficients

The pattern of path coefficients is determined in part by the number of lags included (see Figure 1). Thus, lag-1 paths are from a variable in one wave to a variable in the next wave, whereas lag-4 paths are from a variable in Wave 1 (Year 5) to a variable in Wave 4 (Year 9). Our a priori path model

(Figure 1) included these paths: from Year 4 (the last year of primary school) to all subsequent variables in the next five years (the first five years of secondary school); autocorrelation (horizontal) test-retest paths from variables (Years 5–9) in one wave to variables in subsequent waves (lags 1–4); cross-paths from measures (Years 5–9) of one construct to a different construct in the next two waves (lag-1 and lag-2 paths).

In preliminary analyses (Models 1A–4A in Supplemental Materials Table 1) we explored how many lags were needed to fit the data. In the most parsimonious model (Model 1A, Supplemental Materials Table 1) only lag-1 paths were included—paths from each variable to that variable in the next wave only. However, this model provided a poor fit to the data ($CFI = .871$, $TLI = .775$). In Model 2A, we added paths from the two primary-school (Year 4) variables to all variables in Years 5–9 (rather than only lag-1 paths to just the Year 5 variables). The fit of Model 2A ($CFI = .943$, $TLI = .857$) was substantially improved, indicating the need for more than just lag-1 paths, but was still marginal. In Models 3A and 4A we also added lag-1 to lag-4 paths for the cross-paths (Model 3A) and for the autocorrelation paths (Model 4A). Consistent with our a priori model, Model 4 (with lag 1–4 autocorrelation paths but only lag-1 and lag-2 cross-paths) provided an excellent fit to the data ($CFI = .995$, $TLI = .982$).

Support for developmental equilibrium

In the next set of models (Models 5A and the Integrated ASC Model in the Supplemental Materials Table 1) we added invariance constraints to Model 4A to test the a priori assumption of developmental equilibrium (that the paths are consistent over waves). In our a priori model, the most parsimonious of these models (the Integrated ASC Model in Table 1), there was complete invariance of autocorrelation- and cross-paths, across all waves. Because only lag-1 paths were included for the cross-paths, only lag-1 paths were held invariant (e.g., $MSC\ wave_i \rightarrow Test\ Scores\ wave_{i+1} = MSC\ wave_{i+1} \rightarrow Test\ scores_{i+2}$). However, for autocorrelation paths all Lag 1–4 paths were included. For example, not only were lag-1 paths included (e.g. $MSC\ wave_i \rightarrow MSC\ wave_{i+1} = MSC\ wave_{i+1} \rightarrow MSC\ wave_{i+2}$), but also lag-2 paths (e.g. $MSC\ wave_i \rightarrow MSC\ wave_{i+2} = MSC\ wave_{i+1} \rightarrow MSC\ wave_{i+3}$), lag-3 paths and lag-4 paths. The fit of Integrated ASC Model ($CFI = .989$, $TLI = .979$) was excellent. The fit of Integrated ASC Model differed little from that of Model 4 with no invariance constraints (ΔCFI

= .006, $\Delta\text{TLI} = .003$, $\Delta\text{RMSEA} = .004$), providing support for the more parsimonious model in relation to typical guidelines (e.g., $\Delta\text{CFI} < .01$).

An Alternative Approach

In an alternative approach to this same issue, we fitted an alternative set of models in which the school level was always posited to reflect the BFLPE (the "B" version of each model in Supplemental Table 2) rather than a null structure in which no level 2 variables were specified. Interestingly, each of these B models fitted better than the corresponding A model. This issue was already evident in the set of A models in which the fit of the Integrated ASC Model with the BFLPE structure at Level 2 (the school level) fitted the data marginally better than the corresponding Model 5 with a null structure at Level 2. The explanation is that the fit for the BFLPE structure at the school level was so good, and even better than the fit at Level 1, that when the structures at Level 1 and 2 were combined, the fit was even better than that at Level 1 alone. For the present purposes, we feel that the A versions of the models are more relevant, in that they focus specifically on the fit of Level 1, where the relevant issues are what lags are needed and what invariance constraints are accepted. However, the results of the two sets of analyses are relevant, and both lead to the Integrated ASC Model, which is the basis of subsequent results and analyses presented in the main text of the article.

Supplemental Table 2

Goodness of Fit for Alternative REM Path Models of Pretest (Year 4) Variables, and the Autocorrelation and Cross Paths (Following From Figure 1)

Model	Chi-Sq/df	RMSEA	CFI	TLI	Year 4	Autocorrelation	Cross-paths	Multi-Level Structure
No Invariance Constraints								
1A	5808/ 78	.148	.871	.775	Lag-1	Lag-1-NoInv	Lag-1-NoInv	Null
1B	5802/ 94	.134	.930	.878	Lag-1	Lag-1-NoInv	Lag-1-NoInv	BFLPE
2A	2574/ 54	.118	.943	.857	All	Lag-1-NoInv	Lag-1-NoInv	Null
2B	2768/ 54	.107	.967	.922	All	Lag-1-NoInv	Lag-1-NoInv	BFLPE
3A	541/ 70	.075	.988	.942	All	Lag-2-NoInv	Lag-2-NoInv	Null
3B	623/43	.063	.992	.971	All	Lag-2-NoInv	Lag-2-NoInv	BFLPE
4A	134/ 18	.044	.997	.980	All	All-NoInv	Lag-2-NoInv	Null
4B	170/ 34	.044	.998	.991	All	All-NoInv	Lag-2-NoInv	BFLPE
Invariance Constraints added to Model 4								
5A	505/ 66	.044	.990	.980	All	All-Inv	Lag-1-NoInv	Null
5B	557/ 82	.041	.994	.988	All	All-NoInv	Lag-1-Inv	BFLPE
Integrated ^a	557/ 82	.041	.994	.988	All	All-NoInv	Lag-1-Inv	BFLPE

Note. ChiSq = chi-square; df = degrees of freedom ratio; CFI = Comparative fit index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation. BFLPE = big-fish-little-pond effect. See Figure 1 for a representation of the path model. Year 4 = Paths from Year 4 (primary school) variables; lag-1 = only paths to Year 5 variables, All = paths to all variables in Years 5–9; autocorrelation = test-rests (horizontal) paths from one variable to the same variable in subsequent years; lag-1 = paths to the adjacent Year; NoInv = no invariance constraints; Inv = invariance across lags; Cross = Cross-paths from one construct to a different construct. For each of the first five models the same model was fitted without the BFLPE structure at the school level (the A version of the model with the Level 2 structure left empty) and with the BFLPE structure (the B Version).

^a This is referred to as the "Integrated" ASC Model, given that all subsequent analyses are based on it. A priori path coefficients include paths: from Year 4 (pretest) to all subsequent variables; autocorrelation (horizontal) test-retest path measures (Years 5–9) in one wave to all subsequent waves (lags 1–4); cross-paths from measures (Years 5–9) of one construct to a different construct in the next wave (lag-1 and Lag-2). One latent school factor—school-average achievement based on school-average math grades (Year 4), school track, and school-average test scores. The Integrated ASC Model is the same in Model 5A with the BFLPE added to form Model 5B.

Supplemental Materials Section 4:**The I/E model (Hypothesis 1)—Extended Analyses of the Effects of Year 4 Variables with Controls for Intervening Variables (Following from Table 3 in the Main Text)**

It is also of interest to see predictions from the Year 4 math and German grades, to math school grades and test scores in Years 5–9, although these were not the primary focus of these analyses. Year 4 math grades are consistently positively predictive of math grades in Years 5–9 (paths = .418 to .338), and even more predictive of math test scores in Years 5–9 (paths = .587 to .559). Paths from math grades in Year 4 to math grades in Years 5–9 differed significantly from each other (Wald [df = 4] = 11.97, $p = .018$), becoming somewhat smaller over time (Table 2A). However, paths from Year 4 math grades to test scores in Years 5–9 were remarkably stable over time, and did not differ significantly from each other (Wald [df = 4] = 4.90, $p = .298$).

Paths from Year 4 German grades are much less predictive of math test scores in Years 5–9 (paths = .093 to .190) and particularly, of math grades (paths = -.089 to .007). The contrast between the paths based on the Year 4 math and German grades respectively, supports the construct validity and domain specificity of the Year 4 grades.

It is also interesting to note that test scores in Years 5–9 are more highly correlated with primary school math grades (Year 4) than with secondary school grades (Years 5–9). This pattern of results is consistent with the rationale for Hypothesis 1, in relation to correlations among these variables, suggesting that Year 4 grades based on untracked schools behave more like test scores in Years 5–9 than do school grades in highly tracked schools. (In these Supplemental Materials we present extended analyses of this issue, evaluating the effects of Year 4 grades controlling for intervening variables.)

An alternative in the evaluation of Hypothesis 2 is to evaluate the effects of Year 4 grades on Years 5–9 outcomes, controlling for intervening variables. The question then becomes

what are the effects of Year 4 school grades on, for example, Year 9 MSC after controlling for the effects of MSC, math school grades, and math test scores from Years 5–8. Of course, the effects of Year 4 variables on Year 5 outcomes are the same as those already discussed (see Table 2 in the main text), as there are no intervening variables. However, for example, the effects on school grades in Year 4 on Year 6 outcomes would be the direct effects of the Year 4 outcomes beyond what is mediated through Year 5 variables. Hence, effects in Table 2A (no intervening variables) are the total effects, whilst those in Table 2B are direct effects after controlling for intervening variables.

The direct effects of Year 4 math grades continue to be positive for Year 6 MSC (.156) as well as for the positive effects on Year 5 MSC (path = .428), whereas paths to MSC in Years 7–9 are non-significant. This indicates that there are new, additional effects of Year 4 math grades on Year 6 MSC beyond the effects that can be explained in term of MSC, test scores and grades in Year 5. In subsequent Years 6–9, there are still substantial effects of Year 4 math grades, but these are mediated through outcomes in intervening years (i.e., the total effects in Table 2A are substantial).

The pattern of results based on Year 4 German grades is quite different. Again the negative effects of Year 4 German grades on Year 5 MSC are the same as already observed, with no intervening variables (path = -.333). However, there continue to be new, statistically significant negative effects on MSCs in Years 5–8 (-.233, -.144, -.071, respectively). It is only in Year 9 that the negative effects of Year 4 German grades are no longer statistically significant (path = -.066, SE = .036). These new effects of Year 4 German grades in Years 7 and 8 apparently are due to the fact that intervening variables during secondary school years do not include measures of German achievement, which would mediate the effects of Year 4 German grades.

Although this was not a primary focus of the present investigation, it is also of interest to evaluate the corresponding effects of Year 4 grades on test scores and grades from Years 5–9, controlling for intervening variables. Of particular interest is the result that both Year 4 German and math grades continue to have a positive effect on test scores in Years 5–9, even after controlling for intervening variables. In contrast, the positive effects of Year 4 math grades on subsequent math grades are limited to Years 5 and 6, whereas there are no positive effects of Year 4 German grades on subsequent math grades.

Supplemental Materials Section 6:

BFLPEs: The Negative Effects of School-Average ACH (Hypothesis 4)—Extended Discussion and Analysis

Extended Discussion: Rationale for Tests of the BFLPE

In tests of the BFLPE we focused on school rather than class as the unit of analysis. Indeed, schools were also used as the sampling unit in the original sample design. Also, because students were not consistently in the same class with the same classmates across school years, the definition of classes in relation to contextual effects was not straightforward. In addition, the school-tracking variable, given the nature of tracking in Germany, is naturally a school-level variable. Finally, it is important to note that within schools, students are not streamed by class in relation to ability—only at the school level.

In the terminology of the Marsh, Lüdtke, et al. (2009 & 2012) taxonomy of contextual models, in our study school-average achievement is considered to be a manifest variable that is not centered within groups or schools (implicit or explicit). This is appropriate, in that school-average achievement was based on a single score, and all students within the school were tested (i.e., there was little or no sampling variability in their estimation). In this case, as emphasized by Marsh et al. (2009), controlling for within-school sampling variability as a measure of sampling error based on the latent aggregation of student level (L1) achievement to represent school-average (L2) achievement would be inappropriate and would produce potentially biased results. Indeed, because sampling ratios were high in most schools, it is reasonable to argue that the manifest measure of school-average achievement was measured without sampling error.

Here we used manifest models of the BFLPE, rather than doubly latent models, such as those described by Marsh, Lüdtke et al. (2009). The reason is that for even the simplest contextual models, based on a single wave of data, it is recommended to have at least 50 and preferably as many as 100 schools. Where the number of schools is relatively small (43 in our study), simulation studies by Marsh, Lüdtke et al. have demonstrated a trade-off between bias and accuracy, such that manifest models are likely to be more accurate. Here, school grades, test scores, and school track were naturally manifest variables, whereas the multiple self-concept items could have been used to form a

latent MSC variable. However, particularly because MSC was highly reliable, controlling for measurement error would have had little effect on BFLPEs. Nevertheless, it would be desirable for future studies to include even more schools than were considered here. Also, our focus was on the BFLPE and ASC over this early-to-middle adolescent period, but there is also a need to extend this research to include developmental trends in other outcomes, including long-term effects on academic achievement, aspirations, and educational attainment.

Juxtaposition Between Reflected Glory (Assimilation) and Social Comparison (Contrast) Effects

Some previous research (Marsh, Köller and Baumert (2001; also see Marsh, Kong & Hau, 2000) suggests that there might be some reflected glory associated with being in the most advanced track when the tracking is explicit rather than de facto. Indeed, this suggestion is consistent with theoretical accounts of the BFLPE, which suggest that it is the amalgamation of larger negative (social comparison, contrast) effects and smaller (reflected glory, assimilation) effects. In the present investigation, support for this suggestion would require that the effects of school track are positive after controlling for the negative effects of school-average achievement. However, due in part to the very high correlations between measures of school-average achievement and school track, there was no support for this hypothesis. Hence, support for reflected glory effects associated with attending academically selective schools remains elusive. However, further research specifically designed to evaluate possible reflected glory effects should incorporate specific measures to assess reflected glory (e.g., Marsh, Kong & Hau, 2000; Trautwein, et al., 2009), rather than inferences based on the residual effects associated with school track, after controlling for school-average achievement.

Supplemental Materials Section 7:

Eighteen New Theoretical Predictions Derived From the Integration of the Three Theoretical Models of ASC Formation and Developmental Equilibrium

(1) I/E and REM (ASC-A → ASC-B → ACH):

(1.1) ASC in domain A has a negative effect on achievement in domain B, mediated by ASC in domain B.

(1.1A) These effects are consistent over time (Developmental Equilibrium).

(1.2) Verbal ASC has a negative indirect effect on math achievement.

(1.2A) These effects are consistent over time (Developmental Equilibrium).

(2) I/E and REM (ACH → ASC → ASC → ACH):

(2.1) Achievement in domain A has a negative effect on achievement in domain B, mediated by ASC in domains A and B.

(2.1A) These effects are consistent over time (Developmental Equilibrium).

(2.2) Verbal achievement has a negative indirect effect on math achievement.

(2.2A) These effects are consistent over time (Developmental Equilibrium).

(3) BFLPE and I/E:

(3.1) Group-average achievement in domain A has a positive effect on ASC in domain B, mediated by ASC in domain A.

(3.1A) These effects are consistent over time (Developmental Equilibrium).

(3.2) Group-average verbal achievement has a positive indirect effect on math ASC.

(3.2A) These effects are consistent over time (Developmental Equilibrium).

(4) BFLPE, I/E, and REM:

(4.1) Group-average achievement in domain A has a positive indirect effect on individual achievement in domain B, mediated by ASC in domain A and ASC in domain B.

(4.1A) These effects are consistent over time (Developmental Equilibrium).

(4.2) Group-average math achievement has a positive indirect effect on individual verbal achievement.

(4.2A) These effects are consistent over time (Developmental Equilibrium).

(4.3) Group-average verbal achievement has a positive indirect effect on individual math achievement..

(4.3A) These effects are consistent over time (Developmental Equilibrium).

Note: ASC = academic self-concept; ACH = Achievement; I/E = Internal/External Frame of Reference Model; REM = Reciprocal effects model; BFLPE = big-fish-little-pond effect. Because verbal self-concept and verbal achievement tests were not collected as part of the present investigation, not all of these predictions are testable with the data available. They do, however, illustrate the heuristic importance of integrating the three theoretical models, in that new theoretical predictions emerge that could not be derived from any component of the Integrated ASC Model considered separately.

Section 8: Mplus Syntax Used to Test the Integrated ASC Model (see Supplemental Materials, Section 2)

Mplus syntax

```

TITLE: PALMA BFLPE w0-w5
DATA:FILE =
MPLUS PALMA BFLPEX8 MZP1-6 4OCT2015 w1-5list.dat;      type= imputation;
VARIABLE:
NAMES ARE
ASC1,ASC2,ASC3,ASC4,ASC5
MTSTN1,MTSTN2,MTSTN3,MTSTN4,MTSTN5,
MGRD0,MGRD1,MGRD2,MGRD3,MGRD4,MGRD5,
DGRD0 Mxtrk MmTSTN1 MMGRD0

usevariables are
ASC1,ASC2,ASC3,ASC4,ASC5
MTSTN1,MTSTN2,MTSTN3,MTSTN4,MTSTN5,
MGRD0,MGRD1,MGRD2,MGRD3,MGRD4,MGRD5,
DGRD0 Mxtrk MmTSTN1 MMGRD0 ;

useobservations are (MLATETRK NE 1) AND (LLATETRK NE 1);

CLUSTER = TRSCHLID;

within = MTSTN1,MTSTN2,MTSTN3,MTSTN4,MTSTN5,
MGRD0,MGRD1,MGRD2,MGRD3,MGRD4,MGRD5, DGRD0
;
between = MmTSTN1 Mxtrk MMGRD0 ;
missing are all (-999);

define:
standardize
MGRD0 DGRD0 ;
MMGRD0 = CLUSTER_MEAN(MGRD0);
MmTSTN1 = CLUSTER_MEAN(mTSTN1);
! Mxtrk = CLUSTER_MEAN(MXTRK);

ANALYSIS:
ESTIMATOR=mlr;TYPE = twolevel; !complex
PROCESSORS = 4;

model:
%within%
MTSTN2,MTSTN3,MTSTN4,MTSTN5;

!!!!!!within wave corrs!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
ASC2,ASC3,ASC4,ASC5 pwith MTSTN2,MTSTN3,MTSTN4,MTSTN5;
ASC1 ASC2,ASC3,ASC4,ASC5 pwith MGRD1,MGRD2,MGRD3,MGRD4,MGRD5;
MTSTN1 MTSTN2,MTSTN3,MTSTN4,MTSTN5 pwith MGRD1,MGRD2,MGRD3,MGRD4,MGRD5;

!!!!!! L1 component of BFLPE !!!!!!!!!!!!!!!
! ASC1,ASC2,ASC3,ASC4,ASC5 on DGRD0 (bwd1-bwd5) ;

!!!!!! HOIZONTAL PATHS !!!
ASC2 on ASC1(L1PSCSC1);
ASC3 on ASC2(L1PSCSC1)
ASC1(L1PSCSC2);
ASC4 on ASC3(L1PSCSC1)
ASC2(L1PSCSC2)
ASC1(L1PSCSC3);
ASC5 on ASC4(L1PSCSC1)

```

```

ASC3(L1PSCSC2)
ASC2(L1PSCSC3)
ASC1(L1PSCSC4);

```

```

MGRD2 on MGRD1(L1PGRGR1);
MGRD3 on MGRD2(L1PGRGR1)
MGRD1(L1PGRGR2);
MGRD4 on MGRD3(L1PGRGR1)
MGRD2(L1PGRGR2)
MGRD1(L1PGRGR3);
MGRD5 on MGRD4(L1PGRGR1)
MGRD3(L1PGRGR2)
MGRD2(L1PGRGR3)
MGRD1(L1PGRGR4);

```

```

MTSTN2 on MTSTN1(L1PSACAC1);
MTSTN3 on MTSTN2(L1PSACAC1)
MTSTN1(L1PSACAC2);
mtstn4 on MTSTN3(L1PSACAC1)
MTSTN2(L1PSACAC2)
MTSTN1(L1PSACAC3);
MTSTN5 on MTSTN4(L1PSACAC1)
MTSTN3(L1PSACAC2)
MTSTN2(L1PSACAC3)
MTSTN1(L1PSACAC4);

```

!!!!!!! Effects of pretest variables !!!!!!!!!!

```

ASC1,ASC2,ASC3,ASC4,ASC5 on MGRD0 ;
ASC1,ASC2,ASC3,ASC4,ASC5 on DGRD0 ;

```

```

MGRD1,MGRD2,MGRD3,MGRD4,MGRD5 on MGRD0 ;
MGRD1,MGRD2,MGRD3,MGRD4,MGRD5 on DGRD0 ;

```

```

MTSTN1 MTSTN2,MTSTN3,MTSTN4,MTSTN5 on MGRD0 ;
MTSTN1 MTSTN2,MTSTN3,MTSTN4,MTSTN5 on DGRD0 ;

```

```

ASC1 WITH MTSTN1;
MGRD0 with DGRD0 ;

```

```

!!! CROSS PATHS !!!!
ASC2 on MTSTN1(L1PACSC1);
ASC3 on MTSTN2(L1PACSC1)
MTSTN1(L1PACSC2);
ASC4 on MTSTN3(L1PACSC1)
MTSTN2(L1PACSC2);
! MTSTN1(L1PACSC3);
ASC5 on MTSTN4(L1PACSC1)
MTSTN3(L1PACSC2);
! MTSTN2(L1PACSC3)
! MTSTN1(L1PACSC4);

```

```

MTSTN2 on ASC1(L1PSSCAC1);
MTSTN3 on ASC2(L1PSSCAC1)
ASC1(L1PSSCAC2);
mtstn4 on ASC3(L1PSSCAC1)
ASC2(L1PSSCAC2);
! ASC1(L1PSSCAC3);
MTSTN5 on ASC4(L1PSSCAC1)
ASC3(L1PSSCAC2);
! ASC2(L1PSSCAC3)
! ASC1(L1PSSCAC4);

```

```

MGRD2 on MTSTN1(L1PACGR1);
MGRD3 on MTSTN2(L1PACGR1)

```

```

MTSTN1(L1PACGR2);
MGRD4 on MTSTN3(L1PACGR1)
MTSTN2(L1PACGR2);
! MTSTN1(L1PACGR3);
MGRD5 on MTSTN4(L1PACGR1)
MTSTN3(L1PACGR2);
! MTSTN2(L1PACGR3)
! MTSTN1(L1PACGR4);

```

```

MTSTN2 on MGRD1(L1PSGRAC1);
MTSTN3 on MGRD2(L1PSGRAC1)
MGRD1(L1PSGRAC2);
mtstn4 on MGRD3(L1PSGRAC1)
MGRD2(L1PSGRAC2);
! MGRD1(L1PSGRAC3);
MTSTN5 on MGRD4(L1PSGRAC1)
MGRD3(L1PSGRAC2);
! MGRD2(L1PSGRAC3)
! MGRD1(L1PSGRAC4);

```

```

ASC2 on MGRD1(L1PGRSC1);
ASC3 on MGRD2(L1PGRSC1)
MGRD1(L1PGRSC2);
ASC4 on MGRD3(L1PGRSC1)
MGRD2(L1PGRSC2);
! MGRD1(L1PGRSC3);
ASC5 on MGRD4(L1PGRSC1)
MGRD3(L1PGRSC2);
! MGRD2(L1PGRSC3)
! MGRD1(L1PGRSC4);

```

```

MGRD2 on ASC1(L1PSSCGR1);
MGRD3 on ASC2(L1PSSCGR1)
ASC1(L1PSSCGR2);
MGRD4 on ASC3(L1PSSCGR1)
ASC2(L1PSSCGR2);
! ASC1(L1PSSCGR3);
MGRD5 on ASC4(L1PSSCGR1)
ASC3(L1PSSCGR2);
! ASC2(L1PSSCGR3)
! ASC1(L1PSSCGR4);

```

```
%between%
```

```

schlmn by Mxtrk*-1; !(FL1);
schlmn by MMGRD0*1; !(FL1);
schlmn by MmTSTN1@1; !(FL1);
Mxtrk *0.01;
MMGRD0 *0.01;
MmTSTN1 *0.01;

```

```
!
```

```

ASC1,ASC2,ASC3,ASC4,ASC5 ON schlmn (BBM1-BBM5);
! ASC1,ASC2,ASC3,ASC4,ASC5 ON mMGRD0 (BBM1-BBM5);
! ASC1,ASC2,ASC3,ASC4,ASC5 ON Mxtrk (BBM1-BBM5);
! ASC1,ASC2,ASC3,ASC4,ASC5 ON MmTSTN1 (BBM1-BBM5);

```

```

! ASC1,ASC2,ASC3,ASC4,ASC5 with ASC1,ASC2,ASC3,ASC4,ASC5;
ASC2 ON ASC1;
ASC3 ON ASC2;
ASC4 ON ASC3;
ASC5 ON ASC4;

```

```

Model Constraint:
!orthogonal Polynomial Contrasts

```

```

new (cons1);
cons1 = ((2 * BBM1) + (1 * BBM2) + (0 * BBM3) + (-1 * BBM4) + (-2 * bbm5))/10;
new (cons2);
cons2 = ((2 * BBM1) + (-1 * BBM2) + (-2 * BBM3) + (-1 * BBM4) + (2 * bbm5))/14;

new (cons3);
cons3 = ((-1 * BBM1) + (2 * BBM2) + (0 * BBM3) + (-2 * BBM4) + (1 * bbm5))/10;

new (cons4);
cons4 = ((1 * BBM1) + (-4 * BBM2) + (6 * BBM3) + (-4 * BBM4) + (1 * bbm5))/70;

```

```

!pairwise comparisons;
new (cons6);
cons6 = ((-1 * BBM1) + (-1 * BBM2) + (-1 * BBM3) + (-1 * BBM4) + (4 * bbm5))/5;
new (cons7);
cons7 = ((-1 * BBM1) + (-1 * BBM2) + (-1 * BBM3) + (-1 * BBM5) + (4 * bbm4))/5;
new (cons8);
cons8 = ((-1 * BBM1) + (-1 * BBM2) + (-1 * BBM5) + (-1 * BBM4) + (4 * bbm3))/5;
new (cons9);
cons9 = ((-1 * BBM1) + (-1 * BBM5) + (-1 * BBM3) + (-1 * BBM4) + (4 * bbm2))/5;
new (cons10);
cons10 = ((-1 * BBM5) + (-1 * BBM2) + (-1 * BBM3) + (-1 * BBM4) + (4 * bbm1))/5;

```

```

OUTPUT: svalues TECH1; stdyx; tech4; sampstat mod(ALL);
MODEL RESULTS

```

Mplus Results (an Extended Version of Parameter Estimates Presented in Table 1 of the Main Text)

Two-Tailed
Estimate S.E. Est./S.E. P-Value

Within Level

ASC2 ON

ASC1	0.452	0.013	35.995	0.000
MTSTN1	0.112	0.018	6.294	0.000
MGRD1	0.137	0.016	8.764	0.000
MGRD0	0.175	0.041	4.225	0.000
DGRD0	-0.198	0.036	-5.551	0.000

ASC3 ON

ASC2	0.452	0.013	35.995	0.000
ASC1	0.160	0.017	9.554	0.000
MTSTN2	0.112	0.018	6.294	0.000
MTSTN1	-0.020	0.022	-0.900	0.368
MGRD2	0.137	0.016	8.764	0.000
MGRD1	0.008	0.018	0.462	0.644
MGRD0	0.030	0.036	0.831	0.406
DGRD0	-0.124	0.027	-4.540	0.000

ASC4 ON

ASC3	0.452	0.013	35.995	0.000
ASC2	0.160	0.017	9.554	0.000
ASC1	0.077	0.024	3.244	0.001
MTSTN3	0.112	0.018	6.294	0.000
MTSTN2	-0.020	0.022	-0.900	0.368
MGRD3	0.137	0.016	8.764	0.000
MGRD2	0.008	0.018	0.462	0.644
MGRD0	0.032	0.042	0.757	0.449
DGRD0	-0.083	0.036	-2.311	0.021

ASC5 ON

ASC4	0.452	0.013	35.995	0.000
ASC3	0.160	0.017	9.554	0.000
ASC2	0.077	0.024	3.244	0.001
ASC1	0.072	0.030	2.420	0.016
MTSTN4	0.112	0.018	6.294	0.000
MTSTN3	-0.020	0.022	-0.900	0.368
MGRD4	0.137	0.016	8.764	0.000
MGRD3	0.008	0.018	0.462	0.644
MGRD0	0.033	0.038	0.876	0.381
DGRD0	-0.034	0.038	-0.901	0.368

MGRD2 ON

MGRD1	0.465	0.016	29.729	0.000
MTSTN1	0.171	0.018	9.604	0.000
ASC1	0.065	0.014	4.597	0.000
MGRD0	0.129	0.030	4.254	0.000
DGRD0	-0.067	0.024	-2.782	0.005

MGRD3 ON

MGRD2	0.465	0.016	29.729	0.000
MGRD1	0.185	0.018	10.272	0.000
MTSTN2	0.171	0.018	9.604	0.000
MTSTN1	-0.090	0.026	-3.494	0.000
ASC2	0.065	0.014	4.597	0.000
ASC1	-0.034	0.019	-1.739	0.082
MGRD0	0.032	0.034	0.945	0.345
DGRD0	-0.023	0.030	-0.760	0.447

MGRD4 ON

MGRD3 0.465 0.016 29.729 0.000
 MGRD2 0.185 0.018 10.272 0.000
 MGRD1 0.133 0.026 5.164 0.000
 MTSTN3 0.171 0.018 9.604 0.000
 MTSTN2 -0.090 0.026 -3.494 0.000
 ASC3 0.065 0.014 4.597 0.000
 ASC2 -0.034 0.019 -1.739 0.082
 MGRD0 -0.036 0.026 -1.367 0.172
 DGRD0 -0.059 0.030 -1.979 0.048

MGRD5 ON

MGRD4 0.465 0.016 29.729 0.000
 MGRD3 0.185 0.018 10.272 0.000
 MGRD2 0.133 0.026 5.164 0.000
 MGRD1 0.066 0.033 2.020 0.043
 MTSTN4 0.171 0.018 9.604 0.000
 MTSTN3 -0.090 0.026 -3.494 0.000
 ASC4 0.065 0.014 4.597 0.000
 ASC3 -0.034 0.019 -1.739 0.082
 MGRD0 -0.038 0.030 -1.238 0.216
 DGRD0 -0.017 0.034 -0.495 0.620

MTSTN2 ON

MTSTN1 0.479 0.013 36.745 0.000
 ASC1 0.038 0.009 4.264 0.000
 MGRD1 0.043 0.008 5.154 0.000
 MGRD0 0.250 0.022 11.331 0.000
 DGRD0 0.128 0.021 6.012 0.000

MTSTN3 ON

MTSTN2 0.479 0.013 36.745 0.000
 MTSTN1 0.204 0.013 15.225 0.000
 ASC2 0.038 0.009 4.264 0.000
 ASC1 -0.007 0.011 -0.574 0.566
 MGRD2 0.043 0.008 5.154 0.000
 MGRD1 0.004 0.011 0.317 0.751
 MGRD0 0.131 0.022 5.965 0.000
 DGRD0 0.063 0.023 2.791 0.005

MTSTN4 ON

MTSTN3 0.479 0.013 36.745 0.000
 MTSTN2 0.204 0.013 15.225 0.000
 MTSTN1 0.087 0.019 4.707 0.000
 ASC3 0.038 0.009 4.264 0.000
 ASC2 -0.007 0.011 -0.574 0.566
 MGRD3 0.043 0.008 5.154 0.000
 MGRD2 0.004 0.011 0.317 0.751
 MGRD0 0.113 0.018 6.183 0.000
 DGRD0 0.090 0.017 5.169 0.000

MTSTN5 ON

MTSTN4 0.479 0.013 36.745 0.000
 MTSTN3 0.204 0.013 15.225 0.000
 MTSTN2 0.087 0.019 4.707 0.000
 MTSTN1 0.046 0.016 2.949 0.003
 ASC4 0.038 0.009 4.264 0.000
 ASC3 -0.007 0.011 -0.574 0.566
 MGRD4 0.043 0.008 5.154 0.000
 MGRD3 0.004 0.011 0.317 0.751
 MGRD0 0.079 0.019 4.108 0.000
 DGRD0 0.053 0.015 3.419 0.001

ASC1 ON

MGRD0 0.486 0.036 13.569 0.000
 DGRD0 -0.264 0.044 -6.058 0.000

MGRD1 ON

MGRD0 0.418 0.033 12.689 0.000

DGRD0 0.007 0.028 0.261 0.794

MTSTN1 ON

MGRD0 0.587 0.027 21.629 0.000

DGRD0 0.093 0.034 2.763 0.006

ASC1 WITH

MTSTN1 0.222 0.019 11.509 0.000

MGRD1 0.315 0.022 14.212 0.000

MGRD0 WITH

DGRD0 0.654 0.080 8.130 0.000

ASC2 WITH

MTSTN2 0.071 0.012 5.659 0.000

MGRD2 0.214 0.022 9.586 0.000

ASC3 WITH

MTSTN3 0.067 0.013 5.337 0.000

MGRD3 0.293 0.020 14.538 0.000

ASC4 WITH

MTSTN4 0.049 0.010 4.967 0.000

MGRD4 0.272 0.019 14.612 0.000

ASC5 WITH

MTSTN5 0.050 0.009 5.367 0.000

MGRD5 0.243 0.017 14.121 0.000

MTSTN1 WITH

MGRD1 0.249 0.019 13.326 0.000

MTSTN2 WITH

MGRD2 0.045 0.013 3.583 0.000

MTSTN3 WITH

MGRD3 0.051 0.013 3.931 0.000

MTSTN4 WITH

MGRD4 0.038 0.012 3.324 0.001

MTSTN5 WITH

MGRD5 0.026 0.013 2.011 0.044

Means

MGRD0 0.000 0.109 0.000 1.000

DGRD0 0.000 0.112 0.000 1.000

Intercepts

MTSTN1 -0.023 0.044 -0.522 0.602

MTSTN2 0.020 0.029 0.692 0.489

MTSTN3 0.011 0.018 0.601 0.548

MTSTN4 -0.010 0.021 -0.489 0.625

MTSTN5 -0.047 0.019 -2.452 0.014

MGRD1 -0.076 0.040 -1.895 0.058

MGRD2 -0.085 0.033 -2.608 0.009

MGRD3 -0.268 0.031 -8.729 0.000

MGRD4 -0.088 0.029 -3.017 0.003

MGRD5 -0.087 0.026 -3.391 0.001

Variances

MGRD0 1.000 0.081 12.371 0.000

DGRD0 1.000 0.082 12.176 0.000

Residual Variances

ASC1 0.880 0.027 32.563 0.000

ASC2 0.712 0.029 24.309 0.000

ASC3 0.679 0.024 28.135 0.000

```

ASC4 0.648 0.025 26.202 0.000
ASC5 0.594 0.018 32.457 0.000
MTSTN1 0.581 0.023 25.662 0.000
MTSTN2 0.336 0.015 22.726 0.000
MTSTN3 0.304 0.015 19.992 0.000
MTSTN4 0.223 0.009 26.178 0.000
MTSTN5 0.228 0.013 16.894 0.000
MGRD1 0.797 0.028 28.859 0.000
MGRD2 0.555 0.028 20.156 0.000
MGRD3 0.676 0.025 27.573 0.000
MGRD4 0.623 0.023 26.750 0.000
MGRD5 0.585 0.023 24.965 0.000

```

Between Level

```

SCHLMN BY
MXTRK -1.324 0.097 -13.695 0.000
MMGRD0 1.335 0.084 15.889 0.000
MMTSTN1 1.000 0.000 999.000 999.000

```

```

ASC1 ON
SCHLMN -0.251 0.080 -3.128 0.002

```

```

ASC2 ON
SCHLMN 0.033 0.121 0.268 0.788

```

```

ASC3 ON
SCHLMN 0.033 0.087 0.376 0.707

```

```

ASC4 ON
SCHLMN -0.005 0.066 -0.074 0.941

```

```

ASC5 ON
SCHLMN -0.167 0.066 -2.540 0.011

```

```

ASC2 ON
ASC1 1.116 0.269 4.150 0.000

```

```

ASC3 ON
ASC2 0.813 0.256 3.179 0.001

```

```

ASC4 ON
ASC3 0.752 0.142 5.298 0.000

```

```

ASC5 ON
ASC4 1.052 0.265 3.977 0.000

```

```

Intercepts
MXTRK 2.093 0.131 16.012 0.000
MMTSTN1 -0.105 0.100 -1.043 0.297
MMGRD0 0.399 0.128 3.122 0.002
ASC1 -0.007 0.040 -0.177 0.860
ASC2 -0.172 0.037 -4.684 0.000
ASC3 -0.303 0.051 -5.935 0.000
ASC4 -0.081 0.070 -1.153 0.249
ASC5 -0.004 0.122 -0.037 0.971

```

```

Variances
SCHLMN 0.374 0.059 6.342 0.000

```

```

Residual Variances
MXTRK 0.081 0.029 2.758 0.006
MMTSTN1 0.039 0.013 3.015 0.003
MMGRD0 0.022 0.019 1.155 0.248
ASC1 0.014 0.007 2.138 0.033
ASC2 0.002 0.005 0.351 0.725
ASC3 0.008 0.004 1.988 0.047
ASC4 0.000 0.002 0.124 0.901

```

ASC5 0.005 0.003 1.673 0.094

New/Additional Parameters

CONS1 -0.013 0.018 -0.743 0.457
 CONS2 -0.066 0.023 -2.855 0.004
 CONS3 0.016 0.039 0.413 0.680
 CONS4 -0.005 0.011 -0.428 0.669
 CONS6 -0.096 0.056 -1.698 0.089
 CONS7 0.067 0.071 0.946 0.344
 CONS8 0.104 0.079 1.325 0.185
 CONS9 0.104 0.114 0.914 0.361
 CONS10 -0.180 0.082 -2.183 0.029