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Moderation of the Big-fish-little-pond Effect: Juxtaposition of Evolutionary (Darwinian-economic) and Achievement Motivation Theory Predictions Based on a Delphi Approach

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Abstract

The big-fish-little-pond effect (BFLPE), the negative effect of school/class-average achievement on academic self-concept, is one of educational psychology's most universal findings. However, critiques of this research have proposed moderators based on achievement motivational theories. Nevertheless, because these motivational theories are not sufficiently well-developed to provide unambiguous predictions concerning moderation of the BFLPE and underlying social comparison processes, we developed a Theory-Integrating Approach; bringing together a panel of experts, independently making theoretical predictions, revising the predictions over several rounds based on independent feedback from the other experts, and a summary of results. We pit a priori hypotheses derived from achievement motivation theories against the more parsimonious a priori prediction that there is no moderation based on previous BFLPE empirical research and Darwinian-economic theory (N = 1,925 Hong Kong students, 47 classes, M age = 12). Consistent with both BFLPE research and Darwinian perspectives, but in contrast to achievement motivation theory predictions, the highly significant BFLPE was not moderated by any of the following: prior achievement, expectancy-value theory variables, achievement goals, implicit theories of ability, self-regulated learning strategies, nor social interdependence theory measures. Although we cannot "prove" that there are no student-level moderators of the BFLPE, our synthesis of social comparison posited in the BFLPE theory and an evolutionary perspective, support BFLPE’s generalizability. We propose further integration of our Theory-Integrating Approach with traditional Delphi methods, combining quantitative and qualitative approaches to develop a priori theoretical predictions and identify limitations in existing theory as an alternative form of systematic review.

Keywords: Big-fish-little-pond effect; social comparison processes; academic self-concept; Achievement motivation theory; Darwinian economics; Theory-Integrating Delphi method

The self-concept construct has a long history in social science research, but particularly in educational settings (Marsh, 2007). Marsh and O'Mara (2008; Morin et al., 2015; Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015) showed that academic self-concept (ASC) formed in high school contributes to the prediction of key academic outcomes and long-term educational attainment, even after controlling the effects of school grades, standardized achievement tests, IQ, and socioeconomic status.

An Educational-Psychology Perspective on the Big-Fish-Little-Pond Effect (BFLPE)

ASC, one's academic self-beliefs and perceptions of competence in different academic domains is based in part on social comparison processes. Thus, ASC depends not only on one's own academic accomplishments but also on how these compare with the accomplishments of one's classmates. These processes explain many seemingly paradoxical findings that have important implications for theory, research, and policy/practice. In particular, one of the most widely studied phenomena in ASC research is the seemingly paradoxical and controversial big-fish-little-pond effect (BFLPE). Marsh (1984; 2007) developed the theoretical model underpinning the BFLPE that integrates diverse theoretical perspectives from many disciplines, based in part on social comparison theory (Festinger, 1954). According to the BFLPE, students who attend schools and classes where the average ability level is high will have lower ASCs than do equally able students who attend mixed- or low-ability classes and schools; a negative effect of class/school-average achievement on ASC. Similarly, academically disadvantaged students who move from special classes for disadvantaged students to main-stream classes with mixed-ability students will suffer diminished ASCs – a negative effect of class-average ability (Tracey et al., 2003).

The BFLPE

Originally described as "paradoxical" in relation to popular beliefs about selective schools and classes, Marsh and Seaton’s (2015; also see Marsh, Kuyper et al., 2014; Marsh, Martin et al., 2017; also see Fang, et al., 2018;) extensive review of BFLPE research based on many individual and cross-national studies across many countries led them to conclude that the BFLPE is a universal phenomenon, one of psychology's most cross-culturally robust findings. In particular, there is excellent support for this premise from data collected by the Organization for Economic Cooperation and Development (OECD) Program for International Student Assessment (PISA). PISA data consist of nationally representative samples of 15-year-olds. Based on four cycles of PISA data (2000-2012), the effect of school-average achievement on ASC was negative in all but one of the 191 samples, and significantly so in 181 samples (Marsh, & Hau, 2003:

103,558 students from 26 countries; Seaton, Marsh, & Craven, 2009, 2010: 265,180 students from 41 countries; Nagengast, & Marsh, 2012: 397,500 students from 57 countries; Marsh et al., 2018: 485,490 students from 68 countries).

Moderators of the BFLPE

A critically important approach for extending BFLPE research, theory, and policy/practice implications is to test whether any student-level motivation variables moderate the BFLPE (see Dai & Rinn, 2008). Seaton et al. (2010) noted that moderation is a double-edged sword. Finding strong moderators of the BFLPE would help understand the underlying processes of the BFLPE and allow the development of personalized interventions that could lessen its negative consequences. However, if the BFLPE generalizes across diverse student characteristics, then such evidence would strengthen support for the BFLPE's theoretical basis, robustness, and claims of universality.

One of the earliest proposed moderators of the BFLPE was individual achievement. In what Marsh et al. (2018) referred to as the *bright student hypothesis*, some researchers argued that BFLPEs should be substantially smaller, eliminated, or even reversed for the brightest students in each class. According to this hypothesis, being the brightest student in high-ability classes should enhance – not diminish–ASC (e.g., Coleman & Fults, 1985; also see Davis, 1966; Huguet et al., 2009). However, according to the theoretical model underpinning the BFLPE (Marsh, 1984; Marsh, 2007), the size of the BFLPE should be similar for the best and worst students within each class. According to the BFLPE theory, the frame-of-reference is established by the class-average achievement. However, the class-average is necessarily the same for all students within a given class. Thus, if the class-average achievement increases, then the ASCs of all students will decrease. Conversely, if the class/school-average achievement goes down, the ASCs of all students will increase. Hence, according to BFLPE theory, the size of the BFLPE should be similar for all students within the same class or school. A growing body of empirical research (Marsh, 1984; Marsh, Kuyper et al., 2014; Marsh, Seaton et al., 2008; Marsh, Martin, et al., 2017) supports these predictions in that interactions between school-average and individual student achievement are consistently small or non-significant, and not even consistent in direction.

Of course, it is not possible for any one study, or even a finite set of studies, to prove that there are no moderators of the BFLPE. However, in one of the most extensive studies of the generalizability of the BFLPE, Seaton, Marsh, et al. (2010; also see review by Marsh & Seaton, 2015) tested the moderation of the BFLPE for math self-concept in relation to individual student differences on 16 potential moderators based on PISA 2003 data (41 countries, 10,221 schools, 265,180 students). Potential moderators in their study included socio-economic status (parental occupation, parental education, home educational resources, and cultural possessions), individual ability, intrinsic and extrinsic motivation, self-efficacy, study methods (elaboration, memorization, and control strategies), anxiety, competitive and cooperative learning orientations, sense of school belonging, and student-teacher relationships.

The BFLPE for math self-concept was not substantially moderated by any of these variables. Although interactions with some of these variables were statistically significant (due in part to the huge sample size), none were substantively significant in terms of nullifying or changing the direction of the BFLPE. For example, the BFLPE was significantly larger for students with high levels of anxiety, but students with low levels of anxiety suffered from the BFLPE as well, just to a slightly lesser extent than high-anxious students. For present purposes, we operationalize this logic by evaluating the relative size of the BFLPE and its moderation. Thus, if the size of the moderation is less than half the size of the BFLPE, then the direction of the BFLPE remains consistent even for students who are extreme in terms of the moderator (i.e., two standard deviations above or below the mean of the moderator). Based on the same logic and tests of simple slopes, Seaton, Marsh, et al. (2010) concluded that none of the potential moderators in their study substantially moderated the BFLPE, attesting to its broad generalizability. This research, along with the consistency of BFLPE across countries in extensive cross-national studies, led Seaton, Marsh, and colleagues to posit the BFLPE as one of psychology's most universal phenomena (Seaton, Marsh, et al., 2009, 2010; also see review by Marsh & Seaton, 2015). Nevertheless, this database did not contain the achievement motivation variables that are the focus of our study – particularly achievement goal theory constructs.

Jonkman et al. (2012) took up the challenge to find moderators of the BFLPE for academic self-concept. They posited big-five personality characteristics (extroversion, agreeableness, openness, conscientiousness, and neuroticism) as potential moderators of the BFLPE. However, they also considered narcissism, with the rationale that students high on narcissism (i.e., those with exaggerated feelings of superiority, self-importance, and grandiosity) might be immune to the BFLPE. Neuroticism and narcissism were statistically significant moderators of the BFLPE, whereas interactions with the remaining personality traits were non-significant. However, the sizes of the two significant interactions were small relative to the size of the BFLPE (less than one-quarter the size of the BFLPE). Thus, even students high on narcissism and low on neuroticism experienced the BFLPE, although to a slightly lesser degree than students low in narcissism or high in neuroticism. Nevertheless, Jonkman et al. suggested that the results support the construct validity of the theoretical model underlying the BFLPE, in that students high on narcissism, who were predicted to be less affected by the relative performances of their classmates, experienced significantly smaller BFLPEs. However, they also noted that the results do not translate into intervention programs to counter the BFLPE through fostering a counterproductive construct such as narcissism. In summary, the Jonkman et al. study demonstrated that traditional personality characteristics are not substantial moderators of the BFLPE, and that moderation effects of narcissism remain small relative to the size of the BFLPE.

Achievement Motivation Theories and Potential Moderators of the BFLPE

Although there is growing evidence in support of the robustness of the BFLPE, there continue to be calls for further consideration of potential moderators of the BFLPE and its integration with motivation theories in educational science and educational psychology. In one of the most influential critiques of the BFLPE, Dai and Rinn (2008) argued for the need for a broader conceptualization of the BFLPE that focuses on students having a more active role in regulating their social cognition and motivation. They underlined the need to consider individual student characteristics to better understand the social comparison process underlying the BFLPE, noting that ASC is far removed from the social comparison and motivational process posited to drive it. Knowing the moderators of the BFLPE, they argued, would facilitate the identification of students most vulnerable to the adverse effects of the BFLPE, better placement decisions, and more appropriate interventions. In particular, they argued for better integration of the broad body of “motivation models” – an intentionally broad term referring to diverse achievement motivational theories, processes, and constructs known to be important in educational research that are likely to moderate the BFLPE.

Following from Dai and Rinn’s (2008) critique of BFLPE, good candidates for potential moderators of the BFLPE are motivation constructs (see Table 1) based on key theories of achievement motivation such as expectancy-value theory measures of task-value (importance, interest, usefulness), achievement goal theory measures (mastery, performance-approach, performance-avoidance), implicit theories of ability (fixed-ability beliefs), self-regulated learning strategies (elaboration, rehearsal, control, effort/persistence), and social interdependence theory measures of learning environment preferences (cooperative, competitive). For example, two subsequent studies (Cheng et al., 2014; Wouters et al., 2013) evaluated the extent to which the BFLPE varies as a function of constructs from achievement goal theory (e.g., mastery, performance-approach, and performance-avoidance goals). Although both studies found substantial BFLPEs, moderation effects were small, non-significant, or not consistent with *a priori* predictions in terms of direction. Thus, the BFLPE was slightly larger–not smaller, as predicted– for students who had stronger mastery goals (Cheng et al. 2014; Wouters et al. 2013). Indeed, both studies suggested that endorsement of any motivation goal tended to increase the size of the BFLPE. However, the interaction effects were consistently small (ESs = 0 to -.10) relative to the size of the BFLPE. Despite the plausibility of motivational constructs moderating the BFLPE, the available literature thus far has found little evidence of individual-student-level moderators (see review by Marsh, Martin, et al., 2017; Marsh & Seaton, 2015). As such, in the present research, we aim to undertake a comprehensive investigation of a broad range of motivation constructs based on major motivational theories as potential moderators of the BFLPE.

Students' Approaches to Learning (SAL)

Consistent with Dai and Rinn's focus on "motivation models" in a generic sense, we felt it was important to consider key constructs from various motivation theories. Hence, a critical first step in our research was to select the motivational constructs to consider. Fortunately, the OECD has already developed the SAL instrument (Marsh, Hau et al., 2006). SAL was derived from a rigorous process of selecting educational psychology's most useful constructs and motivation theories, and empirical testing of psychometric properties based on responses to SAL in extensive cross-national pilot studies. These strong psychometric properties were subsequently validated in the use of SAL in nationally representative samples from 26 countries as part of the PISA2000 data collection (Marsh, Hau et al., 2006).

SAL is a brief survey that measures 14 factors from a variety of theoretical perspectives that assess self-regulated learning strategies, self-beliefs (ASC and self-efficacy), expectancies, values, implicit theories of intelligence, goals, and learning preferences. Marsh, Hau, et al. (2006) described how this OECD-SAL instrument provides a standard set of educational measures that have been selected by an OECD expert panel of substantive researchers and that have been validated across the world in extensive pilot studies designed by an OECD expert panel of methodological researchers (see summary by Marsh, Hau et al., 2006). On this basis, Marsh, Hau et al. contended that SAL should be a useful focus in diverse educational research settings, providing the longitude and latitude against which to map new and existing educational constructs and test theoretical predictions -- the starting point for the present investigation. Starting with these constructs, we sought to test moderation of the BFLPE in relation to the two most widely used self-belief constructs; ASC

(Marsh, 2007) and academic self-efficacy (Bandura, 1986). Following from the SAL instrument, we consider the following achievement motivation constructs as our key moderator variables.

Task values. *Task-value measures* (importance, interest, usefulness) were based on Eccles' theoretical model of expectancy-value theory (Wigfield & Eccles, 2000), and the items were adapted from the OECD- SAL instrument (Marsh, Hau et al., 2006). Types of values include attainment value (importance), intrinsic value (e.g., interest, enjoyment), and extrinsic value (e.g., utility, instrumental value).

Achievement goals. A goal is a mental representation of future possibilities that directs proactive behavior (Elliot & Fryer, 2008). In achievement settings, achievement goals influence competence-relevant behaviors. Achievement goal theory measures (mastery, performance-approach, performance-avoidance) were based on the trichotomous achievement goal model and items adapted from Elliot and Church (1997; Elliot, 1999).

The implicit theory of intelligence. An implicit theory of intelligence or ability is the belief that students hold about the stability of their ability. Dweck (2000) proposed that the students who hold an entity theory (fixed belief) believe that ability is unchangeable, whereas those who hold an incremental theory believe that ability is malleable. The measure of fixed-ability beliefs was based on the theoretical model and items adapted from Dweck (2000).

Self-regulated learning strategy. Learning strategies are the strategies that a student adopts in order to acquire knowledge (Zimmerman, 2000). Effort and persistence represent volitional aspects of students' learning. Measures of learning strategies used here (elaboration, rehearsal, control, effort/persistence) were adapted from the OECD-SAL instrument (Marsh, Hau, et al., 2006).

Competitive or cooperative environment preference. Social interdependence theory proposes that the completion of an individual's goals are dependent on the action of others (Johnson & Johnson, 1999). The perceived learning environment is believed to be relevant to students' preferences in learning in a competitive or cooperative environment. In a cooperative learning environment, students work together in teams, whereas in a competitive environment, students' performances are evaluated against each other. Social interdependence theory measures used here (competitive and cooperative), were adapted from the PISA SAL instrument (Marsh, Hau, et al., 2006).

A Darwinian-economic Perspective on the BFLPE

In 1985, economist Robert E. Frank published *Choosing the Right Pond: Human Behavior and the*

Quest for Status—just a year after Marsh and Parker (1984) published the initial BFLPE study. Frank (2012) has since updated his thinking on the relative position and contextual-effects in *The Darwin Economy: Liberty, Competition, and the Common Good.* Based on this evolutionary perspective, Frank argues that social comparison within local contexts—the driving force behind the BFLPE—is a fundamental endowment of human evolution. Frank states, “to survive and prosper, an individual need not be the strongest, fastest, or smartest animal in the universe. He may be weak, slow, and stupid. What matters is that he be able to compete successfully against members of his own species vying for the same resources” (p.24). In this economic research literature, there are many examples of social comparison and frame-of-reference effects like those in BFLPE studies. The most widely studied effects are those of income and unemployment on subjective well-being. Thus, for example, subjective well-being is positively affected by one's own income but negatively affected by the income of one's reference group due to social comparison (Clark, 2018). Nevertheless, there has been surprisingly little cross-citation between these economic studies based on the evolutionary perspective and educational studies of the BFLPE.

Frank's (2012) position is that the tendency to compare ourselves to immediate others is a fundamental and largely unalterable aspect of our human nature. Frank's perspective is similar to Festinger's (1954) perspective that social comparison is a universal human drive with critical survival advantages. Thus, Festinger (1954, p. 117) notes that "there exists, in the human organism, a drive to evaluate his opinions and his abilities." For Frank, social comparison is a universal process that is a means to achieve the survival of the fittest, not a trait per se. As an economist, Frank does not talk explicitly about individual-level moderation, but he does claim that social comparison is universal. For Frank, social comparison is not something that can be eliminated, reduced, or controlled. Instead, society needs to build environments that restrain the more destructive aspects of social comparison processes. Because of the ubiquity and survival advantages of social comparison, moderation of social comparison processes (the basis of the BFLPE) by individual differences is likely to be small and inconsequential. From this Darwinian perspective, we would also expect individual-level moderators of the BFLPE to be small and practically insignificant. Instead, our expectation is that moderating effects will primarily be at the level of the school and school system, which can have major consequences for the reference group that children experience on a daily basis (e.g., how academically selective a school system is; Parker, Dicke, et al., 2018).

Importantly, we note that the focus of Frank's research on the universality of social comparison processes is relevant to the social comparison processes that underpin the BFLPE. Specifically, his theoretical perspective is consistent with claims for the universality of the BFLPE based on empirical research (e.g., Marsh & Seaton, 2015; Marsh, Martin, et al., 2017) and the proposal that individual student variables are unlikely to moderate the BFLPE substantially. Hence, the theoretical underpinning of Frank's economic research and BFLPE research in educational psychology research are very similar. Thus, it is relevant to align these two areas of research, particularly as thus far, there has been almost no cross-fertilization between them.

The Present Investigation

The Genesis of the Present Investigation

The present investigation originated in a question-answer session at the International Congress of Applied Psychology. In a key-note presentation on goal theory by one of the main architects of goal theory, the first author of the present investigation asked him to comment on a prediction that goal theory constructs would moderate the BFLPE. Although not resolved at the conference, they agreed to collaborate in pursuit of the resolution of this issue. Because they came from different theoretical perspectives, they decided to select an intentionally diverse group of colleagues to work with– a total of nine co-authors from Australia, the USA, Europe, and Asia. In this sense, the co-authors were chosen explicitly as a panel of experts representing a diverse range of interests, theoretical perspectives, and expertise in educational science, psychology, and motivation science (representing six universities from four continents) who agreed to collaborate on this project.

Our first task was to select an appropriate database to test our predictions. An ideal database would include particularly the key goal theory constructs, as well as other achievement motivation constructs, such as those in the SAL instrument (although the SAL instrument was the basis of the PISA2000 data collection, these data did not contain measures of goal theory that were of particular relevance). However, the appropriate database also had to be suitable for testing the BFLPE (see Marsh & Seaton, 2015; Marsh, Martin, et al., 2017, for requirements to test the BFLPE). Although the collective team was not able to locate an ideal database, we collectively judged the one used here to be the most suitable (see subsequent discussion in the Methods section).

Our next task was to generate a priori hypotheses in relation to moderation of the BFLPE based on motivation theories. However, it quickly became apparent that there was disagreement among the authors and that the motivational theories were not yet sufficiently developed in relation to the specific issues considered here to generate unambiguous predictions. For this reason, we developed a systematic process for integrating, revising, and seeking consensus among our diverse group of co-authors – an approach that we subsequently referred to as a "Theory-Integrating Approach".

A Theory-Integrating Approach: Developing Predictions Based on Motivation Theory

Developments of a theory-integrating method. We specially selected co-authors of the present investigation as "experts" representing a diverse range of interests, theoretical perspectives, and expertise in educational science, psychology, and motivation science. For present purposes, we refer to the co-authors as an "expert panel" to emphasize that the co-authors were specifically selected to represent diversity, rather than uniformity, in relation to the key issues.

The individual co-authors began with alternative perspectives on whether key motivation constructs would moderate the social comparison processes underpinning the BFLPE. Using an iterative approach, each author offered independent predictions of which of the constructs would moderate the BFLPE in terms of direction, size, and the rationale. The open-ended responses about the rationale for decisions provided a better basis for revising responses in subsequent rounds, but also provided insight into underlying perspectives based on motivational theory. In this sense, our Theory-Integrating Approach is a hybrid, mixed-method approach. It combines both quantitative and qualitative responses to juxtaposing competing perspectives. Our Theory-Integrating Approach is also an alternative approach to a systematic review in relation to the development of theoretical predictions in areas where existing theory is not sufficiently well-developed to provide sufficiently unambiguous predictions when applied to a specific issue. In this sense, the approach is important in identifying limitations and ambiguities in existing theory and research as well as generating consensus predictions.

Because the co-authors represented four continents, we sent responses from each co-author to all the other co-authors via email. In this sense, the process was iterative. As part of our approach, we summarized the initial quantitative and qualitative responses and returned them to the co-authors for further comment. In each ensuing round, co-authors independently revised their responses based on responses by others as appropriate, offered a rationale for their responses, and commented on their rationale and the rationales offered by others. We continued this iterative process of structured interaction among co-authors until a consensus had been reached, or in a few cases, there were alternative perspectives, and a consensus was not achieved. We contend that this Theory-Integrating Approach is a healthy approach to developing theoretical predictions when there is an initial disagreement. It is also an excellent way to advance theory and research in educational psychology where research is often conducted in silos that do not provide a robust critique of competing perspectives.

Contrasting Sets of Predictions

In the present investigation, following from Dai and Rinn's (2008) critique of the BFLPE, we test predictions based on achievement motivation theories in relation to the moderation of the BFLPE. More specifically, we juxtaposed two perspectives: (1) the highly parsimonious prediction based on previous empirical BFLPE research (e.g., Marsh, Martin, et al., 2017; Marsh & Seaton, 2015) and consistent with a Darwinian-economic theoretical perspective (Frank, 2012) that social comparison processes underpinning the BELPE are universal, and (2) the more nuanced theoretical predictions based on the results of our Theory-Integrating Delphi method, as summarized in Table 1.

Tests of these competing sets of predictions are based on a set of models shown in Figure 1. In the basic BFLPE model (Figure 1A), math self-concept (MSC, the dependent variable) is regressed on individual-student (L1) and class-average (L2) achievement). The BFLPE is the direct effect of L2 achievement after controlling L1 achievement. In Figure 1B, the L1xL2 achievement interaction is added to test the bright student hypothesis (that the individual student achievement moderates the BFLPE such that the BFLPE is less negative for brighter students). In Figure 1C, achievement motivation measures, and their interaction with class-average achievement are added to test predictions in Table 1.

Methods

Sample and Measures

Sample

The data were collected from a sample of Hong Kong secondary school students. Data collection was approved by the Research Panel, Faculty of Education, the Chinese University of Hong Kong; school and student consents were obtained. Students (N=1,925; 47.3% boys, 52.7% girls; 11-16 years old, mean age = 12 years) from the end of the school year in Grade 7 (47 intact classes, 12 schools) were queried regarding their motivation for school learning. The schools were sampled from various districts and broadly differentiated in terms of academic strength. They were broadly representative of Hong Kong such that four schools were selected from each of the above-average, average, and below-average school ability bands.

Measures

As described earlier, self-belief and achievement motivation measures were based in part on the OECD-SAL instrument (also see Supplemental Materials for the wording of the items and the a priori factors to which they are associated). Preliminary factor analyses of responses are summarized below. Achievement was based on a standardized achievement test that was taken by all students in Hong Kong (in July) before the entry of the first year of secondary schooling (Grade 7, in September) and used as one basis for tracking students at the start of secondary school.

Statistical Analyses

Preliminary Factor Analysis

Factor analyses, specifically exploratory structural equation modeling (ESEM; Marsh et al., 2014), were undertaken with Mplus 8 (Muthén & Muthén, 2016) using robust maximum likelihood estimation (MLR). We used SET-ESEM (Dicke, Marsh et al., 2018; Marsh et al., 2019) to alleviate confounding at item level, for between measures of self-beliefs (treated as the outcome variables) and the set of motivational moderator variables listed in Table 1 (the predictor variables posited to moderate the BFLPE). In SET-ESEM, based on the *a priori* model, items are allowed to cross-load on factors within the same set but not on factors from different sets, thus avoiding confounding for constructs within the same set. A set is defined by a group of constructs based on the same motivation theory. For example, the set for achievement goal consists of a mastery goal, performance-approach goal, and performance-avoidance goal. In preliminary analyses, we applied SET-ESEM with target rotation to test the factor structure of these 15 *a priori* latent factors—the two outcomes (MSC and self-efficacy) factors and the 13 achievement motivation variables listed in Table 1. The factor analysis based on 59 indicators designed to measure these factors provided a good fit to the data according to guidelines of goodness-of-fit (e.g., Marsh et al., 1988). Target factor loadings show that all factors are well-defined (see Supplemental Materials for Mplus syntax and further discussion of the psychometric analyses). All subsequent analyses used factor scores based on this preliminary factor analysis.

Multilevel Models

We performed moderation analysis using multilevel modeling with random intercept, fixed slope estimation, with the commercially available MlwiN (Rasbas et al., 2004; also see Marsh, 2016) program. This allowed us to accommodate the two-level hierarchical structure of the data: students (L1) nested within classes (L2). Fixed effects considered in different models (see Figure 1) include the first-order ("main") effects of individual student (linear and quadratic) achievement, class-average achievement, and factor scores representing each of the 13 achievement motivation factors (see Table 1). Interaction effects included the multiplicative terms between class-average achievement and each of the potential moderators of the BFLPE (individual achievement and the 13 achievement motivation factors listed in Table 1). Random effects included the intercepts at the two levels to evaluate class-to-class variation in individual and class-average achievement. Separate analyses were done for each of the 13 achievement-motivation moderators to test the moderation of the BFLPE

To facilitate interpretation of results in relation to a standard effect size metric, we standardized individual student scores (M = 0, SD = 1), including academic achievement and all variables based on factor scores. However, none of the multiplicative effects (quadratic achievement, interactions of class-average achievement with individual achievement, or any of the achievement motivation moderators) or aggregated variables (class-average achievement) were re-standardized; thus, they were kept in the same metric as the individual student variables. This total-group standardization is important because it provides a common metric with which to compare each class, as opposed to within-class standardization (e.g., within-class centering, transforming the mean of each class to be zero).

Results

Here our focus is on potential moderators of the BFLPE in relation *a priori* predictions based on parsimonious predictions (based on BFLPE empirical research and Darwinian-economic theory) that none of these achievement motivation constructs would moderate the BFLPE, and more nuanced predictions based on our interpretations of motivation theories underlying the SAL and achievement-motivation constructs (Table 1). We begin by testing the BFLPE for our two self-belief measures (MSC and math self-efficacy) and then test potential moderators of the BFLPE listed in Table 1.

Big-Fish-Little-Pond-Effect (BFLPE)

Model 1A (Table 2) shows that individual student achievement is substantially related to both math self-concept (.39) and math self-efficacy (.34). In the basic model of the BFLPE (Model 1B, also see Figure 1A), the negative effect of class-average achievement is substantial for both math self-concept (-.34) and math self-efficacy (-.27). In Model 1C the quadratic component of individual achievement is added to the model. Although the quadratic component is statistically significant, adding it has little effect on the size of the BFLPE. In Model 1D the effect of individual student achievement was made random at the class level.

However, this random effect was not significant, indicating that the effect of achievement on both self-belief constructs was consistent across the 47 different classes.

Moderation of the BFLPE by Individual Achievement (the “Bright Student” Hypothesis)

In Model 1E (Table 2; also see Figure 1B), we added the cross-level interaction between individual and class-average achievement to test the "bright student" hypothesis (that the BFLPE should be substantially smaller for the brightest students). However, this interaction (-.07) was not statistically significant, and even the direction of the non-significant interaction was not consistent with the hypothesis. Consistent with a priori predictions based on theory and previous research (see earlier discussion), there is no support for the bright student hypothesis.

Moderation of the BFLPE by Achievement Motivation Constructs

We tested the moderating effect of each of the 13 achievement motivation constructs (see Table 1 for the constructs and *a priori* hypotheses) in a series of 13 separate models (Model 3A-Model 3M in Table 3; also see Figure 1C). Results indicate that none of the 13 interactions between class-average achievement and the 13 moderators were statistically significant.

The BFLPEs in Table 3 are the effects of class-average achievement after controlling for moderators and interaction effects (Figure 1C). Because many of the moderators are substantially correlated with math self-concept, the effect of school-average achievement on MSC (the BFLPE) (Table 3) is smaller after controlling for them. For example, math self-concept and math interest are highly correlated (.86, see Supplemental Materials), so that BFLPE after controlling for interest (-.11) is substantially less than in the corresponding model without controlling for interest (-.33, Table 2). However, even after controlling for interest, the effect of class-average achievement on MSC is still highly significant (-.11, SE = .02). Importantly, for all 13 moderation models, the direct effect of class-average achievement (the BFLPE) remains significantly negative, ranging in size from -.11 to -.38 (M = -.21).

Discussion

Moderation of the BFLPE

Our primary focus is on the ability of a diverse set of motivational variables to moderate the BFLPE or, conversely, the generalizability of the BFLPE in relation to these variables. The findings are easy to summarize in that none of the interactions was statistically significant. These results provide clear support for the extremely parsimonious prediction of no interactions based on Darwinian-economic theory and previous BFLPE research. The results provide no support for more nuanced predictions bases on achievement motivation theories (Table 1; also see related discussion by Dai & Rinn, 2008).

The central rationale of our study is that social comparison is the basis of the BFLPE. Indeed, previous BFLPE research (Huguet et al., 2009; Marsh, Kuyper, et al., 2014) has shown that controlling for social comparison largely eliminated the BFLPE. Reviews (Marsh & Seaton, 2015) of previous empirical BFLPE studies suggest that there are no substantial moderators of the BFLPE at the level of the individual student, even going so far as to suggest that it is a universal, pan-human phenomenon. Frank’s (2012) evolutionary perspective argued that social comparison tendencies are universal. Thus, from these perspectives and consistent with our findings, achievement motivation variables considered here are unlikely to alter social comparison tendencies and, thus, are unlikely to moderate the BFLPE. Hence these distinct research disciplines are consistent with each other as well as the results of the present investigation.

Strengths, Weaknesses, and Directions for Further Research

It is essential to evaluate the strengths and limitations of the present investigation in relation to the corpus of BFLPE studies (see reviews by Fang, et al., 2018; Marsh & Seaton, 2015; Marsh, Martin, et al., 2017). BFLPE studies are now routinely based on appropriate multilevel models that more clearly separate the effects of achievement at the levels of the individual student, the class, and the school (see Marsh, 2007; Marsh & Seaton, 2015 for reviews of the essential design and statistical requirements of BFLPE studies). Most BFLPE studies are based on a single wave of data for a single group, which makes interpretations of generalizability and causality problematic. More robust support for generalizability comes from the growing number of PISA studies showing that BFLPE results generalize over many countries. More defensible support for causality comes from longitudinal designs in which variables are collected in multiple waves (e.g., Marsh, 1991; Marsh, Koller, et al., 2001; Marsh et al., 2000; Marsh, Pekrun et al., 2019; also see review by Marsh & Seaton, 2015).

In a few longitudinal studies (Marsh et al., 2000; Marsh, Pekrun et al., 2019; also see Marsh, Chessor, et al., 1995), analyses were based on the individual student achievement measures from the end of primary school that were used to assign students to different ability tracks. These pre-transition measures provide more robust controls for pre-existing differences and the ordering of variables than do achievement indicators measured after the start of the transition, at the same time as ASC. Several studies described as quasi-experimental (see review by Marsh & Seaton, 2015; Marsh, Pekrun, et al., 2018) provided additional controls in relation to alternative interpretations. Finally, in BFLPE laboratory studies based on true random assignment, Zell and Alicke (2009; see also Alicke et al., 2010) found support for the BFLPE when they experimentally manipulated the frame of reference in relation to feedback given to participants about how their performances compared with others. In summary, there is a convergence of support for the BFLPE interpretations from a wide variety of different studies using multiple methods.

Generalizability of BFLPE Over Motivation Constructs

A particular strength of our study was the theoretically diverse range of achievement motivation measures based upon the OECD-SAL instrument that provides a standard set of motivation measures that have been validated across the world. In their presentation of SAL, Marsh, Hau, et al. (2006) specifically noted the usefulness of this instrument for testing theoretical predictions in relation to a standard set of measures, as we have done here. In this sense, we provide tests of potential moderators of the BFLPE representing important motivation constructs and associated theoretical models from which they are derived. We recognize, of course, that there are inevitably additional motivation-related constructs that we could have considered (e.g., achievement emotions; Pekrun, Murayama, Marsh, Goetz, & Frenzel, 2019). Nevertheless, the comprehensive, systematic, and diverse set of constructs that we have considered is clearly a strength. We also recognize the need to replicate these results in relation to additional data sets representing other countries and different educational systems. However, we do note that our results here are largely consistent with other empirical research based on the BFLPE, including large cross-national studies based in PISA data (see summaries by Fang, et al., 2018; Marsh & Seaton, 2015; Marsh, Martin, et al., 2017).

Design Features

An important design feature of our study is the use of a high-stakes measure of achievement collected before students actually started high school. Because this test had important implications for subsequent tracking of students, it was likely to be taken more seriously by the students than low-stakes tests, which have little or no implications for individual students (e.g., standardized tests in cross-national studies such as PISA). We also note that the inclusion of all students from intact classes avoids many of the limitations associated with sampling variability when school/class-average measures are based on a sample of students. Nevertheless, our study is based on a relatively small number of classes (47) from a single region (Hong Kong) and a single age group over the transition to secondary school. From this perspective, there is a need to evaluate the generalizability of the results with larger, more diverse samples of students. We also note that although the design of the study is longitudinal in relation to achievement and self-concept, it is cross-sectional in relation to self-belief and moderating variables other than prior achievement. From this perspective, it would be useful to collect multiple waves of data and apply more sophisticated statistical models based on the temporal ordering of the variables that more fully test moderation, mediation (e.g., the extent to which intervening variables can explain the BFLPE), and moderated mediation in relation to proximal variables like those considered here as well as more distal outcomes.

Limitations and Directions for Future Research

It is important to emphasize that neither our study nor any finite set of studies can prove that there are no student-level moderators of the BFLPE. Indeed, we have *not* examined all potentially relevant moderators of the BFLPE, even at the individual student level. Even within our more limited focus on motivational moderators, there is room for consideration of additional constructs. Thus, for example, within the expectancy-value framework, our research did not evaluate whether the perceived cost of an activity moderated the BFLPE. Also, we have not thoroughly evaluated self-regulation processes (but see Seaton, et al., 2010, for some relevant research). We also note that different studies are not always consistent in their results. Thus, for example, positive student-teacher relationships were found to be a substantial moderator of the BFLPE in a study by Schwabe et al. (2019), even though a large PISA study by Seaton, Marsh, et al. (2010) showed that it did not moderate the relationship? Hence, even for apparently the same moderator, there is a need for systematic reviews of studies providing inconsistent results. Nevertheless, note that positive social relationships with peers and teachers warrant further research as a potential class-level moderator of the BFLPE. Hence, even for apparently the same moderator, there is a need for systematic reviews of studies providing inconsistent results. Furthermore, student-teacher relationships might be seen as a teacher- or class-level variable, rather than, or in addition to, an individual-student variable. Hence, in further pursuit of this issue, it would be useful to separate the class- and student-level components of student-teacher relationships in appropriate multilevel models (e.g., Marsh, Lüdtke, et al., 2012) and to relate these to the BFLPE.

In the early stages of planning for this study, the collected research team sought the most appropriate dataset to pursue these issues. Critical requirements were that the database had to provide appropriate data to test the BFLPE, and had to provide a reasonable representation of key constructs posited in motivation theory. Although we failed to identify any ideal database, we deemed the database used here to be appropriate. In particular, it provided reasonable data to test the BFLPE and the extent to which motivation constructs –including achievement goal theory constructs – moderated the BFLPE. In particular, the database paralleled the constructs collected in the PISA2000 SAL instrument, described as "OECD's brief self-report measure of educational psychology's most useful affective constructs" (Marsh, Hau, et al., 2005). We note, however, that the data were based on the trichotomous model of achievement goals, rather than subsequent extensions of this model (e.g., Elliot & Hulleman, 2017; Elliot et al., 2011). Nevertheless, in evaluating the suitability of the data set, the team (including two authors of the extended achievement goal theory models) thought that using the trichotomous model was adequate because it focuses on the three most commonly studied and most broadly applicable goals in the achievement goal literature – mastery-approach goals, performance-approach goals, and performance-avoidance goals. These goals are most relevant to our target sample of secondary school students. Nevertheless, we acknowledge that this is a potential limitation of the present investigation and a possible direction for further research.

The rationale used in the present investigation, consistent with much previous research, is to look for substantial moderators. We operationally defined "substantial" as moderators that would neutralize or change the direction of the BFLPE. Thus, high levels of anxiety and neuroticism exacerbate the BFLPE, but even low-anxious and low-neurotic students still suffer the BFLPE. In this sense, the direction – but not the size – of the BFLPE generalizes over levels of anxiety and neuroticism. However, we do not argue that moderation of the BFLPE in relation to anxiety and neuroticism is unimportant. Hence, more emphasis in future research (and systematic reviews) should be placed on the generalizability of effect sizes as well as the direction of the BFLPE.

The focus of BFLPE research and particularly this study has been on psychological moderators of the BFLPE. The major exception to this is individual student level achievement that also failed to moderate the BFLPE. There are, of course, may other non-psychological variables that might moderate the BFLPE. For example, in the present investigation, the students were of similar ages; thus, we were not able to systematically evaluate the generalizability of the BFLPE over an extensive age range (i.e., age as a moderator of the BFLPE). Nevertheless, based on previous research, we know that student age affects the BFLPE. Although the BFLPE has been demonstrated even for very young students at the start of primary school (e.g., Tymms, 2001), there is also evidence that the size of the BFLPE is systematically smaller for very young students (Marsh, Abduljabbar, et al., 2015; Salchegger, 2016). Some research suggests that this reflects developmental-cognitive differences in the ability of young students to form accurate self-perceptions of their competence and the competence of others that are the basis of social comparisons (as suggested by Marsh, Abduljabbar, et al., 2015). However, it also reflects the structure of schooling such that secondary schools are more likely to be stratified as a function of ability than primary schools (as suggested by Parker, Dicke et al., 2018; also see Lohbeck & Möller, 2017; Salchegger, 2016). Further research into how the BFLPE and the social comparison processes underpinning it vary with age is an important direction for further research.

We also stress that the failure to find student-level moderators of the BFLPE interactions does not mean that there are no group-level interactions. Indeed, the theoretical model underpinning the BFLPE assumes that the size of the BFLPE is a function of the extent to which there are systematic between-school differences in school-average achievement; if there are no between-school differences in achievement (i.e., the variance of school-average achievement is zero), the BFLPEs would be predicted to be zero. Thus, Parker, Dicke et al. (2018) demonstrated that the size of BFLPEs across different countries (and over different time waves within the same country) varied systematically with various measures of between-school variation within each country. Hence, the level of differentiation among schools is a moderator of the BFLPE, consistent with the BFLPE theory. Nevertheless, even if school-average achievement were the same for all schools, students would still use social comparison processes. However, the BFLPE would be eliminated because the frame-of-reference (school-average achievement) would be the same for all students in that country. Hence an important direction for further research is to explore further the effects of reducing the ability stratification of schools within a system on the BFLPE and educational outcomes more generally.

BFLPE studies have been based mostly on academic self-belief measures, mainly MSC. Although not our focus, a relevant question is to what extent does the negative effect of class-average achievement (the BFLPE) generalize to other constructs, notably the achievement motivation constructs considered here. In supplemental analyses (Supplemental Materials, Section 4, Table 3), we show that the effect of class-average achievement varies substantially across the achievement-motivation constructs considered here; the BFLPE is only statistically significant for three of 13 motivation constructs: interest (-.24), performance-approach goals (-.18), and performance-avoidance goals (.25; i.e., higher performance-avoidance goals for children who attended classes with higher average achievement). Marsh (2007; Marsh & Seaton, 2015) previously proposed that the size of the BFLPE for different constructs is logically related (in the opposite direction) to the size of the effect of individual student achievement on the construct as an outcome variable. The rationale for this proposal is that if a construct is not systematically related to achievement, then social comparison in relation to achievement is unlikely to have much effect on the achievement motivation variable. Hence, the largest BFLPEs occur for the constructs that are also most highly related to individual student level achievement (Supplemental Materials, Section 4). Thus, for example, the BFLPE is the largest for self-concept and self-efficacy, and these are the two constructs that are most highly related to individual achievement. Indeed, across all 15 constructs (including self-concept and self-efficacy), the correlation between effects of individual student achievement and the BFLPE (the negative effect of class-average achievement) is a remarkable average r = .86. Exploring further this relation between the size of the BFLPE with other constructs and how strongly related the construct is to achievement is an important direction for further research.

Integrating our Theory-Integrating Approach and the Traditional Delphi Method

The name Delphi is based on the Oracle of Delphi, who was able to foresee the future. The traditional Delphi method (e.g., Linstone & Turoff, 1975; Rowe et al., 1991; Sourani, & Sohail, 2015) is used to forecast the future, often contrasting these predictions with those based on theory, time-series trends, and prior research. The process provides optimal integration of diverse perspectives in relation to complex issues where consensus does not exist. The Delphi method assumes that group judgments are more accurate than those of individuals in these situations.

The approach we used to integrate competing perspectives (see earlier discussion) has many similarities to the hallmarks of the Delphi approach; bringing together a group of experts, offering competing theoretical predictions, revising the predictions over several rounds based on written feedback from the other experts, and a summary of the final results. Although the original applications of the Delphi approach were to seek consensus on forecasts for the future, there are many variations with quite different aims. Thus, in the classic overview of the Delphi method, Adler and Ziglio (1996) state that the Delphi method is an exercise in group communication. It intends systematically to enhance informed decision-making by enabling decision-makers to plan based on a broad reservoir of knowledge, experience, and expertise. Alternative aims include generating new ideas, problem-solving, forecasting, policy development, and consensus-building. Thus, for example, Turoff (1970) described the Policy Delphi method to assess social policy and public health in which competing policy alternatives are the focus rather than forecasts of the future. LeBlanc and Baranoski (2011) described a variation of the Delphi method in which the focus was to develop a consensus policy statement in relation to best-practice medical advice. Boyer et al. (2019) described the application of the Delphi approach to develop the core curriculum in a nursing program. Pezaro and Clyne (2015) used the Delphi approach to develop an intervention to support midwives in distress. De Vet et al. (2004) used a variation of the Delphi approach to evaluate determinants of theoretical predictions that led to hypotheses worthy of further examination. A typical aim of the Delphi approach is to reach consensus, but this is not always the case. Thus, in the Argument Delphi technique (Seker, 2015), the focus is to ask experts to create new arguments and critique the arguments of other experts. In this sense, we see our *Theory-Integrating Approach* as a variation of the traditional Delphi approach, along with the host of variants of the Delphi approach that were developed for specific purposes.

Jingle-Jangle Fallacies in Educational Psychology Research

In the present investigation, latent correlations among several of the potential moderators are substantial. This suggests a potential lack of discriminant validity and the possibility of jingle-jangle fallacies (i.e., two constructs that have similar labels might be measuring different constructs, and two constructs that have different labels might be measuring the same construct). In educational psychology, there has been considerable conceptual convergence on the operationalization of constructs such as those considered here. However, there is also an ongoing debate about the degree of overlap between apparently distinct constructs. This is particularly the case for measures coming from different theoretical frameworks and primarily used by different "camps" of researchers who typically do not systematically evaluate how their measures of constructs are related to those used by other researchers. Thus, for example, Marsh (1994) evaluated the factor structure based on two different motivation instruments. The mastery goal scales from the two instruments were highly related and reflected a common underlying factor. However, the competition scale from one instrument reflected a performance orientation primarily, but the competition scale from the other instrument reflected more of a task orientation than a performance orientation. Thus, Marsh (1994; also see Heyman & Dweck, 1992; see Marsh, Craven, et al., 2003) warned researchers to beware of jingle-jangle fallacies, and to pursue construct-validity studies to test interpretations of the measures more vigorously. Similarly, Bong (1996) cautioned that "many researchers are too quick to invent their own set of labels without carefully examining those found in the literature," thus creating "what can be aptly called 'a conceptual mess' for those who try to draw a coherent whole out of the relevant literature" (p. 151).

Given this history, it is not surprising that several of the constructs considered here are substantially correlated (see latent correlation matrix in Supplemental Materials, but also the wording of the items). Not unexpected, perhaps, were the high correlations between academic self-concept and self-efficacy (see Marsh, Pekrun et al., 2019, on the murky distinction between self-concept and self-efficacy), and between performance-approach goals (e.g., "It is important for me to do better than the other students in this subject") and competitive learning (e.g., "I like to try to be better than other students" – see Marsh, Craven, et al., 2003). However, there were also high correlations among mastery goals (e.g., "It is important for me to understand the content of this subject as thoroughly as possible"), importance (e.g., " For me, being good at this subject is very important") and utility value (e.g., "Compared to most of my other activities, what I learn in this subject is very useful"). Although not the focus of the present investigation, we note the need to better clarify the theoretical and predictive distinctiveness of key constructs in educational psychology by evaluating support for convergent and discriminant validity (and jingle-jangle fallacies) when competing theoretical constructs are juxtaposed within the same study. Ideally, this is best accomplished by collaboration among researchers from different theoretical camps seeking to clarify conceptual issues in the measurement and application of different constructs (e.g., Marsh et al., 1997; also see Marsh, Pekrun et al., 2019). We suggest that this might be accomplished by using a systematic approach such as our Theory-Integrating Delphi method to sort our issues in the conceptual overlap and the appropriate measurement of critical constructs.

Conclusions and Implications

In the present investigation, we have stressed the theoretical implications of integrating the extensive BFLPE research literature with Frank's (2012) Darwinian-economic perspective and juxtaposing these with more nuanced predictions based on key motivational theories. The results of the present investigation add to the growing research literature on the robustness of the BFLPE. More specifically, we demonstrated that a range of student motivation variables that might have been predicted to moderate the BFLPE based on achievement motivation theories (Table 1) failed to do so. These results are in line with previous BFLPE research, which has demonstrated the robustness of BFLPEs in relation to potential student-level moderators

(Marsh, Martin, et al., 2017; Marsh & Seaton, 2015). However, our paper does this more systematically in relation to constructs based on achievement-motivation theories. Importantly, we also provide a synthesis with Darwinian-economic perspectives on this robustness. Indeed, even though there has been little cross-referencing between this economic research and BFLPE studies, both have a similar basis in terms of social comparison processes. BFLPE provides further empirical support for the Darwinian-economic perspective, and the Darwinian-economic perspective provides an evolutionary theoretical basis for the robustness of the BFLPE

There are many important implications associated with the BFLPE, social comparison processes, and frame-of-reference effects more generally. We extend theory by integrating theoretical perspective from economics (Darwinian) and educational (BFLPE) research disciplines. We extent BFLPE research by showing the BFLPE generalizes across a diverse set of achievement-motivation variables, contributing to the claim that it is a universal phenomenon (Marsh, Martin, et al., 2017; Marsh & Seaton, 2015)—at least in relation to the achievement-motivation moderators considered here. Concerning educational policy, in many school systems worldwide, high-achieving students are increasingly being taught in academically selective schools. However, the collected body of BFLPE research reviewed here—as well as our results—suggests that this may not be the optimal environment for such students, at least in terms of ASC. Indeed, there is a growing body of research suggesting that the ability stratification that drives the BFLPE also has negative consequences for student achievement and long-term educational attainment (Marsh, 1991; Marsh & O'Mara, 2008). Thus, for example, Parker, et al. (2018) combined five cycles of PISA data to demonstrate that countries with high levels of ability stratification had lower levels of achievement. Furthermore, countries that increased ability stratification over this period also had decreasing levels of academic achievement.

The evolutionary basis for the social comparison processes that underpin the BFLPE has important practical implications. The search for student-level moderators of the BFLPE has been prompted at least in part by the hope that these findings would lead to personalized interventions that would counteract some of the negative consequences of social comparison and the BFLPE (e.g., Dai & Rinn, 2008). Alternatively, Frank (2012) suggests that social comparison processes are inherent, but that there is a need to build environments in which its negative consequences are reduced. Thus, for example, there is clear evidence from PISA studies that the size of the BFLPE in different countries is strongly related to the extent of ability stratification that exists in the different countries (Parker, et al., 2018). Taken to the extreme, if the average ability level is the same in all schools and classes, then there should be no BFLPEs. The lesson to be learned from the Darwinian-economic perspective is that interventions aimed at reducing the negative consequences of the social comparison processes should be aimed at the level of the class, school, school-system, or even the whole country rather than trying to modify the social comparison tendencies of individual students.

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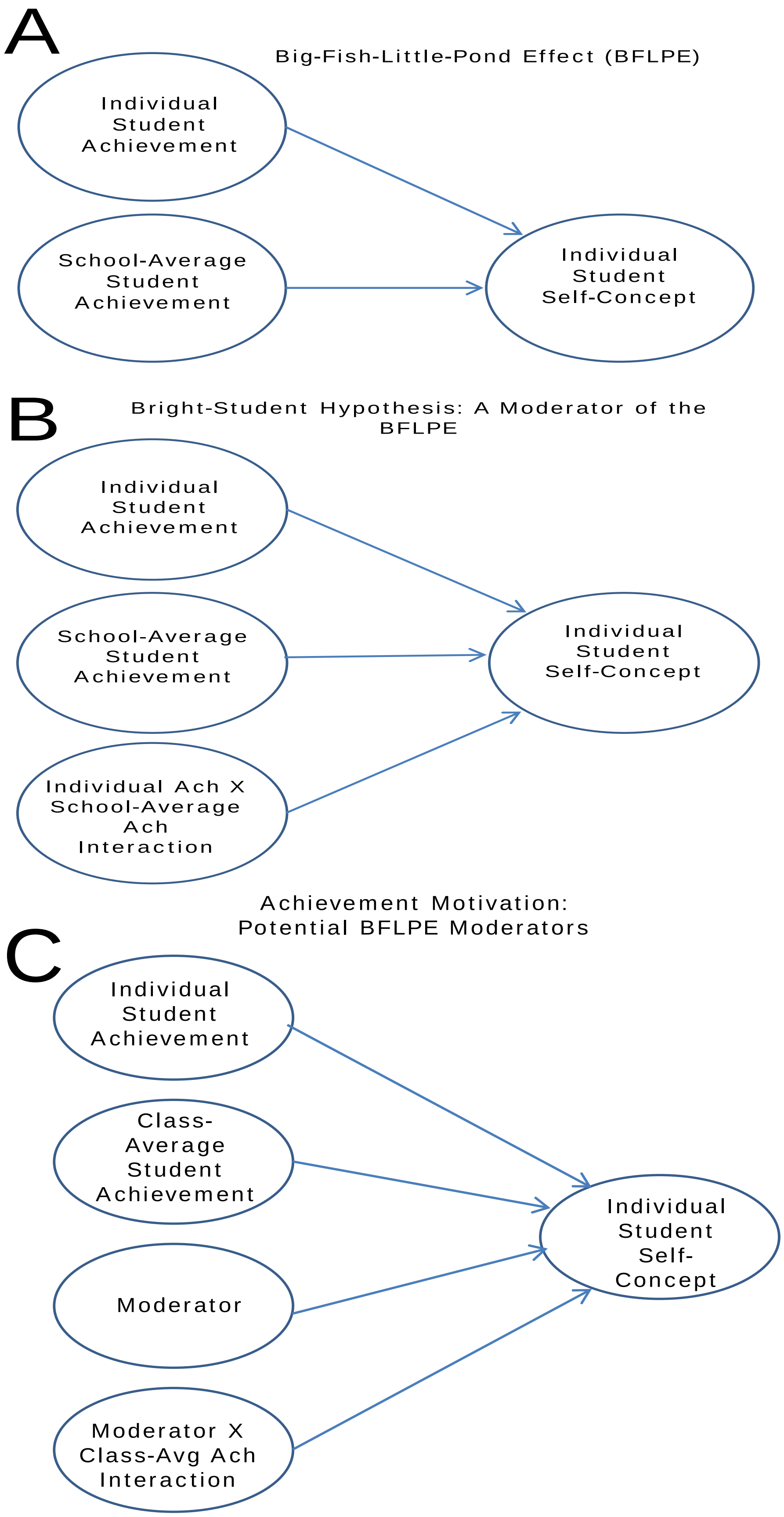

Figure 1. (A) Conceptual model of the BFLPE. (B) BFLPE moderated by individual student achievement. (C) BFLPE moderated by motivation moderator sand individual achievement.

Table 1

Moderators of the BFLPE: A Priori Hypotheses About the Nature Of the Interaction Between the Moderator and Class-Average Achievement in Predicting Math Self-Concept (MSC) Based on Achievement Motivation Theories and BFLPE Research (and Darwinian Perspectives)

Moderator	Achievement motivation theory hypotheses: Predicted interaction (nature, direction, and rationale) when both moderator and Class-average achievement are high:	BFLPE Research (Darwinian)
Mastery goals	Small decrease in BFLPE when class-average achievement and mastery goals are both high (positive interaction); intrapersonal and task-based comparison is salient and social comparison is less important even though the focus on achievement could strengthen the BFLPE	Little or no effect
Performance-approach goals	Moderate increase in BFLPE (negative interaction); due to focus on achievement and social comparison.	Little or no effect
Performance-avoidance goals	Moderate increase in BFLPE (negative interaction); due to focus on achievement and social comparison.	Little or no effect
Fixed Mindset	??? Could increase BFLPE because belief in a fixed ability makes ability relative to others more salient and damaging to MSC, but could also decrease the BFLPE because social comparison is ***less*** salient due to focus on own ability	Little or no effect
Learning preference: Competitive	??? could result in a small increase in BFLPE due to focus on social comparison, but enjoyment of competition and doing better than others might offset the BFLPE.	Little or no effect
Learning preference: Cooperative	Small decrease in BFLPE (positive interaction), due to focus on group-based standards of collective achievement rather than social comparison even though there is a focus on achievements of others).	Little or no effect
Learning strategy: Rehearsal/memorization	??? could result in a small decrease in BFLPE (positive interaction) because use of learning strategies reduces salience of social comparison, but could increase BFLPE due to a shallow learning strategy, low achievement motivation, and low emotional regulation (negative interaction).	Little or no effect
Learning strategy: Metacognitive control	Small decrease in BFLPE (positive interaction), because ability to use control strategies (a) makes social comparison less important, (b) makes it possible to buffer negative effects of social comparison.	Little or no effect
Learning strategy: Elaboration	Small decrease in BFLPE (positive interaction), because use of elaboration and deep processing involves mastery achievement motivation, reduces salience of social comparison.	Little or no effect
Learning strategy: Effort/persistence	Small increase in BFLPE (negative interaction); because trying hard is threatening to MSC and promotes attribution of failure to lack of ability, which makes low ability relative to others salient.	Little or no effect
Task value: Importance	Moderate increase in BFLPE (negative interaction), because importance reflects attainment value and makes achievement salient.	Little or no effect
Task value: Utility value	Small increase in BFLPE (negative interaction), because instrumental value of task makes it important to achieve.	Little or no effect
Task value: Intrinsic value/interest	Moderate increase in BFLPE (negative interaction), because intrinsic value and interest focus attention on mastery, and reduce importance of social comparison.	Little or no effect

Note. Because the BFLPE is negative, negative interactions mean that the size of the negative effect of the BFLPE is decreased (including even a reversal in direction), whereas positive interaction mean that the size of the BFLPE is increased.

??? Indicates that there was no clear consensus or alternative, unreconciled perspectives

Table 2

BFLPEs: Effects of Individual and Class-average Achievement on Math Self-concept and Math Self-Efficacy

	Mod1A		Mod1B		Mod1C		Mod1D		Mod1E	
	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
Self-Concept Fixed Part										
BFLPE			-.34	.07	-.33	.07	-.33	.07	-.35	.07
L1-Achievement-Linear	.39	.03	.43	.03	.45	.03	.45	.03	.45	.03
L1-Achievement-Quad					.05	.02	.06	.02	.08	.02
L1xL2Achievement									-.07	.05
Random Part										
L2: Class Intercept	.10	.02	.06	.02	.06	.02	.06	.02	.06	.02
L2: L1-Ach-Lin							.00	.01		
L1: Student Intercept	.74	.02	.73	.02	.73	.02	.73	.02	.73	.02
-2*log likelihood:	4949		4928		4919		4918		4917	
Self-Efficacy Fixed Part										
BFLPE			-.27	.07	-.27	.07	-.27	.07	-.28	.07
L1-Achievement-Linear	.34	.03	.38	.03	.39	.03	.40	.03	.39	.03
L1-Achievement-Quad					.04	.02	.05	.02	.07	.03
L1xL2Achievement									-.08	.05
Random Part										
L2: Class Intercept	.08	.02	.05	.02	.05	.02	.06	.02	.06	.02
L2: L1-Ach-Lin/CONS							.00	.01	.00	.01
L1: Student Intercept	.76	.03	.76	.03	.76	.03	.76	.03	.76	.03
-2*log likelihood:	5012		4997		4992		4990		4988	

Note. Separate analyses were done for self-concept and self-efficacy. L1 = student level. L2 = class level. Ach = achievement (linear and quadratic components. BFLPE = big-fish-little-pond effect, the effect of class average (L2) achievement. Parameter estimates shaded in gray are statistically significant ($p < .05$). N = 47 classes, 1921 students

Table 3

Moderation of BFLPE by Each of 13 Covariates

Model	Model3A		Model3B		Model3C		Model3D		Model3E		Model3F		Model3G		Model3H		Model3I		Model3J		Model3K		Model3L		`Model3M		
Moderator	Interest		Fixed		Importance		Mastery		PerfAppr		PerfAvd		Memory		Persist		Cooperat		Compet		Useful		Deep		Strategy		M
Fixed Effects	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	S	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	
BFLPE	-.11	.02	-.29	.05	-.35	.06	- .37	.06	-.21	.05	-.22	.06	-.32	.06	-.38	.06	-.35	.06	-.27	.05	-.35	.059	-.29	.05	-.32	.06	-.21
L1-Ach-Lin	.08	.01	.31	.03	.40	.03	.38	.02	.27	.02	.30	.03	.45	.03	.37	.02	.46	.03	.29	.02	.40	.025	.34	.02	.39	.03	.34
L1-Ach-Quad	.01	.01	.06	.02	.06	.02	.06	.02	.05	.01	.03	.02	.05	.02	.05	.02	.06	.02	.04	.01	.05	.017	.04	.02	.05	.02	.05
Moderator	.93	.010	-.74	.03	.40	.02	.46	.02	.67	.02	-.46	.02	.31	.02	.46	.02	.27	.02	.65	.02	.43	.02	.52	.02	.46	.02	.34
Interaction	.02	.01	-.01	.05	.04	.03	.03	.03	-.02	.02	-.05	.03	-.06	.03	.02	.03	-.01	.03	.02	.02	.01	.03	.02	.03	.01	.03	.00
Random Part																											
L2-Class	.01	0.00	.04	.01	.05	.01	.04	.01	.03	.01	.04	.01	.05	.01	.04	.01	.05	.01	.03	.01	.05	.012	.03	.01	.04	.01	.04
L1-Student	.12	.01	.57	.02	.61	.02	.56	.02	.37	.01	.59	.02	.65	.02	.57	.02	.68	.02	.38	.01	.59	.019	.52	.02	.58	.02	.52

Note. L1 = student level. L2 = class level. Ach = achievement (linear and quadratic components. BFLPE = big-fish-little-pond effect, the effect of class average (L2) achievement (shaded in grey). M=mean of effects across all 13 models. Parameter estimates shaded in gray are statistically significant ($p < .05$). Separate analyses were done for each of the achievement-motivation moderators (see Table 1 for more information on the achievement motivations listed under each model). Thus, for Model3A the moderator is interest and the interaction is the effect of the interest by class-average achievement interaction. N = 47 classes, 1921 students

Supplemental Materials:

Section 1 Extended Discussion of Variables Used in the Present Study

This section gives an account of the theory and empirical findings on the achievement motivation moderator variables in their relation between self-concept and academic performance. These constructs are shown in the literature to be closely linked to various desirable academic outcomes and also to have important implications as educational objectives of their own (Baumert, Fend, O'Neil, & Peschar, 1998; Marsh, Hau, Artlet, Baumert, & Peschar, 2006). They are interrelated and collectively represent different aspects and stages of the motivational behavior of school children (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000), therefore are relevant and crucial to answering the research questions in the current study.

Self-Efficacy

Bandura (1994, p. 71) defined self-efficacy as "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives. Self-efficacy beliefs determine how people feel, think, motivate themselves, and behave". Positive self-efficacy is positively related to various outcomes such as achievement behavior, health outcomes, life satisfaction, etc. (A. Bandura, 1986, 1997). Self-efficacy is a multidimensional construct. Academic self-efficacy (Pajares, 2008; Zimmerman, Schunk, & Dibenzedetto, 2017) is closely related to the outcomes of actual tasks such as goal setting, actions, and persistence because the more individuals believe in their abilities, the more likely they will engage with and accomplish a task. Naturally, success in completing the task also reinforces self-efficacy. Self-efficacy is a similar construct to self-concept in that they both measure one’s self-perceptions of ability. Nevertheless, depending on the nature of the instrument used to measure self-efficacy, the influence of the frame of reference effect in self-efficacy could differ dramatically to that observed for self-concept (Marsh, Trautwein, Lüdtke, & Köller, 2008; Marsh & Yeung, 2001). In other words, self-concept and self-efficacy differ not in terms of task specificity but in the reliance on social comparison and relativistic standards of comparison (Marsh et al., 2018). While some researchers’ self-efficacy instruments are very task-specific (e.g., A. Bandura, 1986), others have designed measurements that are more generally defined and less tied to specific tasks (e.g., Judge, Erez, Bono, & Thoresen, 2002). Self-efficacy and self-concept are positively correlated, and both have been found to predict academic performance positively (e.g., Marsh et al., 2006; Marsh & Yeung, 2001). However, in their discussion of the murky distinction between self-concept and self-efficacy, Marsh, Pekrun, et al. (2019) note that many so-called self-efficacy measures are really more like self-concept measures in that they invoke social comparison processes to respond to the item. This murky distinction between self-concept and self-efficacy is particularly relevant here in that Marsh, Pekrun et al. (2019) emphasized that the math self-efficacy measure used in PISA2000 (the basis of the SAL instrument used here) was really more like a math self-concept measure. On this basis we predicted (and found) that the BFLPE for math self-concept would generalize to the math self-efficacy measure used here.

Task Values

Achievement motivation underlies people’s behavior in choosing achievement-related tasks and the persistence and effort invested in carrying out those tasks (Eccles et al., 1983; Wigfield & Eccles, 1992). Types of task values include attainment (importance), intrinsic motivation (e.g. interest, enjoyment), and extrinsic motivation (e.g. utility, instrumental value; Eccles, 2009; Eccles & Wigfield, 2002; Ryan & Deci, 2000; Wigfield & Eccles, 2000, 2002). Attainment value describes the degree of importance an individual places on successful performance of a task. An intrinsically-motivated student tends to conduct learning tasks more effectively as they feel satisfied in the act of carrying out the task itself. Intrinsic motivation does not depend on feedback or external rewards; intrinsically motivated students learn because they find course materials interesting and enjoy them. Extrinsic motivation, such as instrumental motivation, on the other hand, is associated with learning with the aim of immediate or long-term external rewards, such as gaining praise from teachers or finding a job. In order for certain knowledge or skills to be useful, one often needs to reach a certain level of proficiency and, therefore, attainment value and utility value are often closely associated (e.g., Durik, Vida, & Eccles, 2006). For example, even if a student thinks that the study of math is useful in order to become an accountant, without actually learning how to do it, awareness of utility value will not, in itself, be able to produce any effect towards future career development.

Studies found that intrinsic motivation such as interest is positively related to perceptions of academic competence (Gottfried, 1985, 1990; Marsh, et al., 2005), desired academic performance (Ginsburg & Bronstein, 1993; Hardre & Reeve, 2003; Lepper, Corpus, & Iyengar, 2005), and future choices (Durik et al., 2006). Although some researchers found extrinsic motivation to be negatively related to desirable outcomes (Lepper et al., 2005), others observed that extrinsic motivation could also be strongly related to educational adjustment measured by dropout intentions, absenteeism, and educational aspirations (Otis, Grouzet, & Pelletier, 2005), and that extrinsic motivation also predicts course selection, choices, and performance (Eccles, 1994; Eccles & Wigfield, 1995).

Achievement Goals

A goal is a future-oriented objective that one commits to. It directs proactive behavior with "the mental image of the future possibility" (Elliot & Fryer, 2008, p. 245). In achievement-related settings, achievement goals have an influence over performance-related behaviors (Dweck, 1986; Elliot, 1997). Initially, achievement goals were categorized into two types, including mastery goals and performance goals (Dweck, 1986; Nicholls, 1984). When a student approaches school work with a motivation to learn, improve, and develop skills and competence, this student has a mastery goal. A performance goal, on the other hand, focuses more on the demonstration of competence and on outperforming other students. Performance goals can be further sub-divided into performance-approach goals and performance-avoidance goals (Elliot, 1999). Performance-approach goals focus on achieving to demonstrate superior competence, whereas performance-avoidance goals emphasize the avoidance of inadequate performance compared to others.

The relation between different types of achievement goal and achievement-relevant outcomes are not always consistent (Elliot, 2005), but can be summarized as follows. Mastery goals are considered the most desirable goals, and are typically associated with positive outcomes (Elliot, 2005; Meece, Anderman, & Anderman, 2005; Murayama & Elliot, 2009; Pintrich, 2003). Performance-approach goals facilitate academic performance (Church, Elliot, & Gable, 2001; Lopez, 1999; Urdan, 2004; Wolters, 2004), but performance-avoidance goals are typically found to be negatively related to both intrinsic motivation and achievement (Elliot & Church, 1997; Halvari & Kjormo, 1999; Pajares & Valiante, 2001; Zusho, Pintrich, & Cortina, 2005).

The literature suggests that Chinese students tend to adopt performance-approach goals rather than mastery goals (Salili & Lai, 2003), although there is consistent evidence that both mastery goals and performance goals exist among Chinese students and that they are both positively related to academic achievement (Ho & Hau, 2008; Salili & Lai, 2003). Elliot and colleagues (see Elliot, Shell, Bouas Henry, & Maier, 2005) argued that performance-approach goals evoke many of the same positive processes evoked by mastery goals (e.g., effort expenditure, persistence), as both goals represent approach forms of regulation fueled by challenge appraisals. However, the use of others as performance referents in these goals fosters a more external focus on the evaluative environment and on what is needed for optimal motivation.

This pattern of adopting performance-approach goals, as well as mastery goals, is in line with the highly competitive nature of the Chinese education system and the cultural context within which students seek recognition from their parents and teachers by outperforming each other. Although the competitive focus in the performance-approach goal might not be beneficial for the development of intrinsic motivation, in some contexts it does facilitate many other desirable outcomes such as effort and persistence, which are highly valued in Chinese culture.

Social Interdependence Theory of Preferred Learning Environment: Cooperative/Competitive

Social interdependence theory proposes that the completion of an individual's goals are dependent on the action of the others (Deutsch, 1949b; Johnson & Johnson, 1999). Positive and negative social interdependence refers to cooperative and competitive preferences, respectively. Students learn through independent studying or teamwork in which they work with other students in groups. The perceived learning environment is believed to be relevant to students' preferences in learning in terms of a competitive or cooperative environment. In a cooperative learning environment, students work together in teams, whereas in a competitive environment, students' performances are evaluated against each other (Deutsch, 1949a, 1949b; Johnson & Johnson, 1989, 1999; Johnson, Johnson, & Smith, 2007).

Cooperative environments are often found to promote positive outcomes such as academic performance (Law, 2008; Roseth, Johnson, & Johnson, 2008; Slavin, 1980) and intrinsic motivation

(Law, 2008) and self-esteem (Slavin, 1980). However, the effects of a competitive environment on academic performance seem to be less effective in relation to desirable outcomes (Johnson et al., 2007; Roseth et al., 2008). In a fitness program, Marsh and Peart (1988) discovered that a competitive environment could lower the level of self-concept while, conversely, a cooperative environment enhanced it. Also, Johnson et al. (2007) noted that, compared to competitive efforts, cooperation promoted higher self-esteem and self-worth (see also Norem-Hebeisen & Johnson, 1981). That said, it is not the case that competitive learning is straightforwardly negatively related to learning outcomes as, for instance, when the relations between academic achievement, self-concept, and learning environment are studied using cross-sectional, cross-national data, competitive preferences were shown to demonstrate positive relations with performance (Marsh et al., 2006; Seaton, Marsh, & Craven, 2010)

Learning Strategies and Effort Persistence

Learning strategies are the strategies that a student adopts in order to acquire knowledge during the learning process (Zimmerman, 2000). Types of learning strategies include strategies of control, memorizing and planning (Zimmerman, 1990). The use of memorization strategies (also called rehearsal strategies) commonly does not involve much deep processing, but rather simply involves the storing of facts in memory for easy recall. Memorization (rehearsal) strategies can be effective for simple learning tasks and sometimes can facilitate the learning of more complex problems. Elaboration strategies are used to relate new knowledge to existing knowledge. Control strategies involve students' close monitoring and regulations to their learning processes; for instance, a student who uses control strategies often checks whether the learning material from a previous session has been understood before the next learning step takes place.

Students who use learning strategies in their studies are more likely to optimize their learning potential (Boekaerts, 1997; Boekaerts & Cascallar, 2006; Zimmerman, 1990, 2002, 2008) and have higher achievement (Camahalan, 2006; Swalander & Taube, 2007; B. J. Zimmerman & Martinez-Pons, 1988) and a higher level of self-related perceptions (Marsh et al., 2006; Zimmerman & Martinez-Pons, 1990).

Effort and persistence represent volitional aspects of students' learning. High motivation can increase the probability of action, but does not explain whether the action will continue and how much exertion will be devoted to the activity. Volition measures the strength and diligence of the pursuit of an activity (e.g., Corno, 1994; Corno & Mandinach, 1983, 2004; see also O'Neil & Herl, 1998). It was found from cross-cultural samples that both learning strategies and effort persistence are positively related to self-perceptions of ability and achievement measurements (Marsh et al., 2006; see also Marsh et al., 2008; Seaton et al., 2010).

Implicit Theories of Ability.

An implicit theory of ability is the belief that students hold about the stability of their ability. Dweck and Leggett (1988) proposed that the students who hold an entity theory believe that ability is unchangeable (even through hard work), whereas those who hold an incremental theory believe that ability is malleable. Implicit theories of ability are often examined in association with learning goals (Blackwell, Trzesniewski, & Dweck, 2007; Dupeyrat & Mariné, 2005; Dweck, Chiu, & Hong, 1995). Individuals who hold an incremental theory are likely to pursue learning goals, which are positively related to effort and persistence, whereas those who hold an entity theory are less likely to pursue learning goals, expend effort and show persistence. Implicit theories of ability do not necessarily reflect cognitive ability levels but do appear to have an influence on cognitive performance. For example, Blackwell et al. (2007) found that incremental theory supported an upward trajectory of grades based on longitudinal data from a sample of grade 7 students, and that an intervention reinforcing incremental theory led to optimal motivation. Studies examining the effect of teachers' praise found that praise for effort led students to view ability as amenable to improvement, but praise for intelligence encouraged children to view ability as fixed and consequently undermined children's motivation and performance (Mueller & Dweck, 1998). However, there are also studies that found that implicit theories of ability bore no direct relation with achievement (Dupeyrat & Mariné, 2005; Furnham, Chamorro-Premuzic, & McDougall, 2002).

Chinese students are taught by their parents and teachers that they can achieve success through working hard and sometimes even drilling, which will also enhance their abilities eventually. Since ability is seen as a controllable trait by Chinese students in the pursuit of success, it may have a reinforcing relation with motivation and beliefs about their competence (Hau & Ho, in press).

To conclude, each of these psycho-social constructs has a strong theoretical basis in educational psychology and has been shown in previous studies to have associations with self-perception and achievement behavior. Therefore, they can be posited as potential candidates that might moderate frame-of-reference effects in the present study.

Supplemental Table 1.
Summary of Constructs and Wording of Items Associated With Each Construct

Set of Constructs	**label**	
Self-Beliefs		***adapted from PISA SAL Instrument***
Self-concept		
Item1	m18	I do well in tests in this subject.
Item2	m75	I learn things quickly in this subject.
Item3	m84	I'm good at this subject.
Self-efficacy		
Item1	m30	I'm certain I can understand the most difficult material presented in texts.
Item2	m60	I'm confident I can understand the most complex material presented by the teacher.
Item3	m105	I'm certain I can master the skills being taught.
Item4	m123	I'm confident I can do an excellent job on assignments and tests.
Fixed (entity) ability beliefs		***adapted from Dweck, 2000***
Item1	m15	My ability in this subject is something I can't change very much.
Item2	m42	I can learn new things, but I can't really change my basic ability in this subject
Item3	m72	I have a certain amount of ability in this subject, and I really can't do much to change it.
Task value		***adapted from Wigfield & Eccles, 2000***
Importance Items		
Item1	m48	Compared to most of my other activities, it is important for me to be good at this subject.
Item2	m78	For me, being good at this subject is very important.
Interest Items		
Item1	m3	I like this subject very much.
Item2	m81	In general, I find working on the assignments for this subject very interesting.
Usefulness Items		
Item1	m54	Compared to most of my other activities, what I learn in this subject is very useful.
Item2	m99	What I learn in this subject is useful in daily life.
Goal Structure		**adapted from Elliot & Church, 1997**
Mastery goals		
Item1	m21	It is important for me to understand the content of this subject as thoroughly as possible.
Item2	m39	I desire to completely master the material presented in this class.
Item3	m51	I prefer subject material that arouses my curiosity, even if it is difficult to learn.
Item4	m63	I prefer subject material that really challenges me so I can learn new things.
Item5	m108	I want to learn as much as possible in this subject.
Item6	m114	I hope to gain a broader and deeper knowledge of this subject in class.
Performance-approach goal		
Item1	m6	It is important for me to do better than the other students in this subject.
Item2	m24	My goal for this subject is to get a better grade than most of the students.

Item3	m36	I am striving to demonstrate my ability in this subject relative to others in this class.
Item4	m66	I want to do well in this subject to show my ability to my family, friends, teachers, or others.
Item5	m93	I am motivated by the thought of outperforming my peers in this subject.
Item6	m120	It is important to me to do well compared to others in this class.
Performance-avoidance goal		
Item1	m12	I often think to myself, "What if I do badly in this subject?"
Item2	m27	I just want to avoid doing poorly in this subject.
Item3	m33	My fear of performing poorly in this class is often what motivates me.
Item4	m57	I'm afraid that if I ask my teacher a "dumb" question in this class, he/she might not think I'm very smart.
Item5	m69	My goal for this subject is to avoid performing poorly.
Item6	m90	I worry about the possibility of getting a bad grade in this subject.
Social interdependence		***adapted from PISA SAL Instrument***
Cooperative learning		***(PISA)***
Item1	m9	It is helpful to put together everyone's ideas when working on a project.
Item2	m87	I like to work with other students.
Item3	m96	I learn most when I work with other students.
Item4	m117	I like to help other people do well in a group.
Competitive learning		***(PISA)***
Item1	m45	Trying to be better than others makes me work well.
Item2	m102	I like to try to be better than other students.
Item3	m111	I learn faster if I'm trying to do better than the others.
Item4	m126	I would like to be the best at something.
Learning Strategies		***adapted from PISA SAL Instrument***
Rehearsal Strategies		
Item1	s3	When I study, I try to memorize everything that might be covered.
Item2	s9	When I study, I memorize as much as possible.
Item3	s18	When I study, I memorize all new material so that I can recite it.
Item4	s27	When I study, I practice by saying the material to myself over and over.
Control Strategies		
Item1	s6	When I study, I start by figuring out exactly what I need to learn.
Item2	s24	When I study, I force myself to check to see if I remember what I have learned.
Item3	s33	When I study, I try to figure out which concepts I still haven't really understood.
Item4	s42	When I study, I make sure that I remember the most important things.
Item5	s48	When I study, and I don't understand something, I look for additional information to clarify this.
Elaboration/deep processing strategies		
Item1	s15	When I study, I try to relate new material to things I have learned in other subjects.
Item2	s30	When I study, I figure out how the information might be useful in the real world.
Item3	s39	When I study, I try to understand the material better by relating it to things I already know.
Item4	s45	When I study, I figure out how the material fits in with what I have already learned.
Effort and persistence		

Item1	s12	When studying, I work as hard as possible.
Item2	s21	When studying, I keep working even if the material is difficult.
Item3	s36	When studying, I try to do my best to acquire the knowledge and skills taught.
Item4	s51	When studying, I put forth my best effort.

Section 3. Preliminary factor analysis relating items to a Priori Constructs

Factor analyses were undertaken with Mplus 8 (Muthén & Muthén, 2016) using robust maximum likelihood estimator (MLR), with standard errors and tests of fit that were robust in relation to non-normality of observations and the use of Likert responses (e.g., Beauducel & Herzberg, 2006; Muthén & Kaplan, 1985). Although confirmatory factor analysis (CFA) has largely superseded exploratory factor analysis (EFA), a growing body of research shows that CFAs in applied research typically fail to provide an adequate goodness-of-fit and results in biased parameter estimates, due in part to overly restrictive CFAs in which each item loads on only one factor. Marsh et al. (2014) present exploratory structural equation modeling (ESEM) as an integrative framework that incorporates CFA/SEM and EFA as special cases. ESEM provides a good balance between the flexibility of EFA (in relation to measurement models) and the diverse applications possible with CFA/SEM. However, in some applications ESEM might lack parsimony (particularly in large, complex models based on many indicators) and confound constructs that need to be kept separate. Hence, Marsh, Nagengast, et al. (2011; also see Dicke et al., 2018; Marsh, Kuyper, et al., 2014), introduced *set-ESEM* that represents a middle ground between the flexibility of ESEM and the rigor of CFA/SEM. In set-ESEM two or more sets of constructs are modelled within a single model such that cross-loadings are permissible for constructs within the same set of factors (as in ESEM) but are constrained to be zero for factors in different sets (as in CFA). In the present study, it was particularly important that there was no confounding between measures of self-beliefs (treated as the dependent variable) and different set of motivation variables listed in Table 1 (the dependent variables posited to moderate the BFLPE). Applying set-ESEM the final model contained all factors, but constrained cross-loadings to be zero between items in one set and factors in a different set (see Section 3 for Mplus syntax and all the parameter estimates) thus, avoiding construct confounding.

The key constructs in the present investigation belong to six theoretically distinct areas: self-beliefs (self-concept and self-efficacy), task-values constructs (importance, interest and usefulness), goal orientations (mastery, performance and avoidance), implicit theories of ability (fixed-ability beliefs), learning strategies (elaboration, rehearsal, control and effort/persistence), and learning environment preferences (cooperative and competitive). For this reason, it was important to avoid confounding the different constructs in preliminary factor analyses. Hence, the Set-ESEM treated each of these six sets as separate sets such that items such that items from different constructs within the same set were allowed to cross-load in other factors within the same set, but cross-loadings for items from different sets were constrained to be zero.

In applied CFA and SEM studies—particularly for large sample sizes—there is a predominant focus on indices that are sample size independent (e.g., Hu & Bentler, 1999; Marsh, Balla, & McDonald, 1988; Marsh, Hau & Wen, 2004). The Tucker-Lewis Index (TLI) and the Comparative Fit Index (CFI) vary along a 0-to-1 continuum, and values greater than .90 and .95 typically reflect acceptable and excellent fit to the data respectively. For the Root Mean Square Error of Approximation (RMSEA), values of less than .05 and .08 reflect a close fit and a minimally acceptable fit to the data respectively. However, it is important to emphasize that these rough guidelines (Marsh, Hau, & Wen, 2004) need to be complemented by a detailed examination of the parameter estimates in relation to theory, predictions, common sense, and alternative models – in accordance with the approach we used here.

In preliminary analyses, we applied set-ESEM to test the factor structure of these 15 *a priori* factors (the two self-belief factors and the 13 achievement motivation factors) that are the focus of the present investigation (see Table 2). The factor analysis based on 59 indicators designed to measure the 15 *a priori* latent factors provided a good fit to the data and target factor loadings show that all factors are well-defined (Table 2; also see Mplus syntax in Supplemental Materials, Section 3). The factor solution was good in that all 15 factors were well-defined, and the fit was good (Root Mean Square Error of Approximation = .020, confirmatory fit index = .939, Tucker-Lewis index = .929). All subsequent analyses used factor scores based on this preliminary factor analysis.

Supplemental Table 2

Factor Structure of Constructs

	Self Conpt	Self Effic	Inter-est	Impor-tance	Use-ful	Fixed	Per-sist	Contrl Stratgy	Elab-orate	Mem-ory	Mast-ery	Perf Appr	Perf Avoid	Comp-etive	Coop-erat
Factor Loadings															
Item 1	.91	.49	.83	.53	.55	.72	.93	.14	.83	.49	.51	.62	.48	.55	.40
Item 2	.37	.79	.66	.79	.80	.51	.51	.28	.45	.75	.53	.65	.42	.73	.72
Item 3	.83	.75				.00	.41	.53	.63	.76	.48	.73	.47	.62	.85
Item 4		.58					.77	.25	.64	.67	.40	.46	.40	.66	.19
Item 5								.40			.80	.47	.50		
Item 6											.79	.59	.58		
Factor Correlations															
Self-Concept	1.00														
Self-Efficacy	.89	1.00													
Interest	.86	.85	1.00												
Important	.36	.45	.49	1.00											
Useful	.39	.47	.56	.78	1.00										
Fixed	-.41	-.43	-.42	-.07	-.14	1.00									
Persistence	.45	.52	.53	.56	.58	-.22	1.00								
Control Strategy	.39	.47	.48	.40	.50	-.11	.63	1.00							
Elaborate	.51	.57	.54	.42	.49	-.16	.71	.73	1.00						
Memory	.27	.33	.33	.28	.36	-.01	.49	.47	.59	1.00					
Mastery	.44	.57	.62	.81	.82	-.19	.75	.59	.57	.35	1.00				
Perf Approach	.67	.68	.64	.71	.50	-.18	.50	.46	.52	.37	.63	1.00			
Perf Avoidance	-.46	-.37	-.35	.32	.15	.63	.06	.03	-.05	.17	.20	.08	1.00		
Competitive	.66	.75	.67	.74	.70	-.23	.66	.55	.63	.41	.82	.94	.07	1.00	
Cooperative	.22	.32	.32	.35	.43	-.06	.34	.35	.39	.33	.45	.35	.21	.44	1.00
Reliability Estimates															
	.83	*.81*	*.72*	*.68*	*.72*	*.54*	*.85*	*.79*	*.82*	*.79*	*.79*	*.81*	*.65*	*.66*	*.75*

Note. Each of the 15 factors was based on between 2 and 6 items (see Supplemental Table 1 item wording associated with each factor). Factor loadings are a priori target loadings relating each item to its *a priori* factor (See Supplemental Materials for Mplus syntax and full set of parameter estimates).

Section 4. Generalizability of the BFLPE to Other Achievement Motivation Constructs

As a secondary aim, it is also of interest to test the effect of class-average achievement on each of the 13 achievement motivation constructs (Supplemental Table 3; also see Figure 1C), the extent to which the BFLPE generalizes to other motivation constructs. Across the 13 constructs, the effect of class-average achievement is significant for only three: interest (-.24), performance-approach goals (-.18), and performance-avoidance goals (.25). In this later case, performance-avoidance goals were higher in children who attended schools with higher average achievement—all else being equal. Marsh (2007; Marsh & Seaton, 2015) previously speculated that the size of the BFLPE is logically related (in the opposite direction) to the size of the effect of individual student achievement. The rationale for this proposal is that if a construct is not systematically related to achievement, then social comparisons in relation to achievement are unlikely to have much effect on achievement. Thus, here the largest BFLPEs are for self-concept and self-efficacy (Table 2 in main text), followed by interest, performance-avoidance goals, and performance-approach goals (Supplemental Table 3). Similarly, these are the constructs most highly related to individual student level achievement (note that the direction of the effect of individual achievement on performance-avoidance goals is negative so that the direction of the corresponding effect of class-average achievement is positive). Indeed, across all 15 constructs (including self-concept and self-efficacy) the correlation between effects of individual student achievement and class-average achievement is a remarkable $r = .86$.

Supplemental Table 3 Effect of Class-average Achievement on Each of 13 Covariates

Model	M2A		M2B		M2C		M2D		M2E		M2F		M2G		M2H		M2I		M2J		M2K		M2L		M2M	
Outcome	Interest		Fixed		Importance		Mastery		PerfAppr		PerfAvd		Memory		Persist		Cooperat		Compet		Useful		Deep		Strategy	
	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
Fixed Part																										
CONS	.00	.04	.00	.02	.01	.03	.01	.04	.00	.03	.00	.03	.00	.03	.01	.03	.00	.03	.01	.04	.01	.04	.00	.03	.00	.03
BFLPE	-.24	.06	.06	.04	.05	.06	.08	.06	-.18	.06	.25	.06	-.06	.05	.10	.06	.08	.05	-.10	.06	.05	.06	-.09	.06	-.03	.05
L1-Ach-Lin	.38	.03	-.19	.02	.12	.03	.15	.03	.26	.03	-.31	.03	.00	.03	.18	.03	-.02	.03	.25	.03	.12	.03	.20	.03	.13	.03
Random Part																										
Level: class																										
CONS/CONS	.05	.01	.01	.00	.03	.01	.04	.01	.03	.01	.04	.01	.02	.01	.03	.01	.01	.01	.04	.01	.04	.01	.03	.01	.02	.01
Level: StdIdRec																										
CONS/CONS	.73	.02	.30	.01	.78	.03	.82	.03	.82	.03	.70	.02	.82	.03	.81	.03	.78	.03	.84	.03	.76	.03	.81	.03	.74	.02

Note: L1 = student level. L2 = class level. Ach = achievement (linear and quadratic components. BFLPE = big-fish-little-pond effect, the effect of class average (L2) achievement (shaded in grey). see Supplemental Table 1 item wording associated with each factor). Separate analyses were done for each of the outcomes. Thus, for Model3A the outcome is interest and the effects are the effect of L2-Ach and L1-Ach on interest.

Section 5 Mplus Syntax and Output for Factor Analysis used to generate factor scores

```
    TITLE: SET ESEM 15 factors 6 SETs

USEVARIABLES ARE
  M18,M75,M84                        ! Math self-concept (MSC)
  M30,M60,M105,M123                  ! Math self efficacy (MSEff)
  M3,M81                     ! Math Value: Interest (MInt)
  M48,M78                    ! Math Value: Importance (MImpt)
  M54,M99                    ! Math Value: Usefulness (MUsef)
  m15,m42,m72                        ! Fixed Mindset (MMndSetF)
  S12,S21,S36,S51            ! Math Learning Strategy: persistence  (persistence)
  s6 s24 s33 s42 s48         ! Math Learning Strategy: Metacognitive control (MLPCntrStrat)
  s15 s30 s39 s45            ! Math Learning Strategy: Elaborations (MMLPDeep)
  s3 s9 s18 s27,                     ! Math Learning Strategy: Rehearsal/memorization
(MLPMemory)
  m21,m39,m51,m63,m108,m114,         ! Goals: Mastery (MGTMast)
  m6,m24,m36,m66,m93,m120,           ! Goals: Performance-approach (MGTPApp)
  m12,m27,m33,m57,m69,m90            ! Goals: Performance-approach (MGTPAvd)
  m45 m102 m111 m126,                ! Learning preference: Competitive (MComp)
  m9 m87 m96 m117,           ! Learning preference: Cooperative (MCoop)
 ;
     ANALYSIS:  ROTATION =Target; ESTIMATOR = MLR;
  MODEL:
    MSC          by   M18,M75,M84                    M30-m123~0    (*t1);
    MSEff        by   M30,M60,M105,M123       M18-M84~0           (*t1);

    MInt         by   M3,M81                          M48-M99~0 (*t2);
    MImpt        by   M48,M78                M3-M81~0    m54-M99~0 (*t2);
    Muse         by   M54,M99                 M3-M78~0            (*t2);

    MMndSetF      by   m15,m42,m72     ;

    persistence    by   S12,S21,S36,S51                 s6-S27~0   (*t3);
    MLPCntrStrat   by s6 s24 s33 s42 S48        s12-s51~0   s15-S27~0   (*t3);
      MLPDeep     by  s15 s30 s39 s45          s12-s48~0   s3-S27~0   (*t3);
    MLPMemory     by s3 s9 s18 s27,            s12-s45~0             (*t3);

    MGTMast       by   m21,m39,m51,m63,m108,m114           m6-m90~0   (*t4);
    MGTPApp       by   m6,m24,m36,m66,m93,m120   m21-M114~0  m12-m90~0  (*t4);
    MGTPAvd       by   m12,m27,m33,m57,m69,m90   m21-M120~0           (*t4);

    MComp         by   m45 m102 m111 m126,    m9-m117~0 (*t5);
    MCoop         by   m9 m87 m96 m117,       m45-m126~0(*t5);
OUTPUT: sampstat stdyx mod tech4 sval MODINDICES (ALL);
   savedata:
   file is   15factor_stacked.doc;
  SAVE = FSCORES;
```

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
MSC BY				
M18	0.913	0.082	11.069	0.000
M75	0.365	0.095	3.825	0.000
M84	0.825	0.116	7.115	0.000
M30	0.072	0.101	0.713	0.476
M60	-0.025	0.078	-0.324	0.746
M105	0.052	0.074	0.695	0.487
M123	0.224	0.089	2.517	0.012
MSEFF BY				
M30	0.492	0.102	4.816	0.000
M60	0.786	0.080	9.871	0.000
M105	0.751	0.074	10.124	0.000
M123	0.579	0.086	6.709	0.000
M18	-0.134	0.073	-1.833	0.067
M75	0.435	0.098	4.427	0.000
M84	0.019	0.119	0.159	0.874
MINT BY				
M3	0.832	0.022	37.086	0.000
M81	0.664	0.023	29.136	0.000
M48	0.006	0.027	0.244	0.807
M78	0.042	0.022	1.922	0.055
M54	0.011	0.022	0.519	0.604
M99	0.049	0.038	1.308	0.191
MIMPT BY				
M48	0.531	0.063	8.492	0.000
M78	0.787	0.062	12.781	0.000
M3	0.045	0.027	1.651	0.099
M81	-0.051	0.036	-1.411	0.158
M54	0.248	0.079	3.162	0.002
M99	-0.082	0.050	-1.648	0.099
MUSE BY				
M54	0.551	0.086	6.383	0.000
M99	0.801	0.086	9.339	0.000
M3	-0.090	0.033	-2.758	0.006
M81	0.119	0.039	3.063	0.002
M48	0.228	0.066	3.437	0.001
M78	-0.069	0.063	-1.096	0.273
MMNDSETF BY				
M15	0.715	0.042	17.210	0.000
M42	0.512	0.033	15.454	0.000
M72	-0.003	0.045	-0.069	0.945
PERSISTE BY				
S12	0.925	0.073	12.694	0.000
S21	0.508	0.054	9.439	0.000
S36	0.408	0.077	5.327	0.000
S51	0.765	0.048	15.823	0.000
S6	0.133	0.039	3.419	0.001
S24	-0.003	0.038	-0.085	0.932
S33	0.288	0.124	2.319	0.020
S42	0.202	0.048	4.206	0.000
S48	0.044	0.057	0.760	0.447
S15	0.089	0.125	0.712	0.476
S30	-0.017	0.038	-0.456	0.649
S39	0.095	0.051	1.860	0.063

S45	0.006	0.048	0.129	0.897
S3	0.158	0.056	2.815	0.005
S9	0.085	0.031	2.765	0.006
S18	-0.051	0.048	-1.063	0.288
S27	-0.083	0.034	-2.462	0.014
MLPCNTRS BY				
S6	0.144	0.103	1.395	0.163
S24	0.284	0.113	2.526	0.012
S33	0.525	0.287	1.831	0.067
S42	0.247	0.120	2.050	0.040
S48	0.399	0.171	2.336	0.020
S12	-0.179	0.047	-3.785	0.000
S21	0.194	0.113	1.712	0.087
S36	0.362	0.126	2.870	0.004
S51	0.055	0.076	0.721	0.471
S15	-0.132	0.125	-1.055	0.291
S30	0.208	0.066	3.135	0.002
S39	0.101	0.087	1.172	0.241
S45	0.145	0.152	0.954	0.340
S3	0.179	0.133	1.345	0.179
S9	-0.075	0.090	-0.832	0.405
S18	-0.088	0.046	-1.903	0.057
S27	0.201	0.163	1.234	0.217
MLPDEEP BY				
S15	0.829	0.216	3.841	0.000
S30	0.449	0.075	5.963	0.000
S39	0.629	0.100	6.307	0.000
S45	0.636	0.141	4.494	0.000
S12	0.022	0.042	0.524	0.600
S21	0.127	0.100	1.267	0.205
S36	0.153	0.088	1.732	0.083
S51	-0.072	0.094	-0.765	0.444
S6	0.250	0.106	2.354	0.019
S24	0.214	0.095	2.262	0.024
S33	0.033	0.185	0.179	0.858
S42	0.154	0.122	1.258	0.208
S48	0.200	0.163	1.223	0.221
S3	-0.107	0.116	-0.923	0.356
S9	-0.098	0.102	-0.957	0.339
S18	0.126	0.054	2.324	0.020
S27	-0.008	0.144	-0.053	0.958
MLPMEMOR BY				
S3	0.493	0.050	9.921	0.000
S9	0.749	0.033	22.821	0.000
S18	0.764	0.031	24.670	0.000
S27	0.674	0.035	19.214	0.000
S12	0.037	0.037	0.997	0.319
S21	0.004	0.024	0.151	0.880
S36	-0.057	0.029	-1.977	0.048
S51	0.045	0.023	1.934	0.053
S6	0.188	0.034	5.528	0.000
S24	0.311	0.034	9.282	0.000
S33	-0.043	0.044	-0.965	0.335
S42	0.204	0.034	6.047	0.000
S48	0.105	0.037	2.863	0.004
S15	-0.035	0.030	-1.164	0.244
S30	0.077	0.033	2.304	0.021

S39	-0.020	0.032	-0.646	0.518
S45	0.007	0.034	0.218	0.828
MGTMAST BY				
M21	0.508	0.044	11.542	0.000
M39	0.534	0.042	12.734	0.000
M51	0.481	0.038	12.604	0.000
M63	0.403	0.041	9.899	0.000
M108	0.800	0.029	27.838	0.000
M114	0.794	0.031	25.483	0.000
M6	0.020	0.032	0.629	0.529
M24	0.037	0.031	1.180	0.238
M36	-0.065	0.032	-2.022	0.043
M66	0.212	0.040	5.283	0.000
M93	0.199	0.037	5.304	0.000
M120	0.091	0.038	2.419	0.016
M12	-0.035	0.034	-1.041	0.298
M27	-0.031	0.033	-0.939	0.348
M33	0.091	0.034	2.696	0.007
M57	-0.199	0.035	-5.658	0.000
M69	-0.044	0.030	-1.450	0.147
M90	0.110	0.026	4.193	0.000
MGTPAPP BY				
M6	0.619	0.031	20.071	0.000
M24	0.648	0.031	20.776	0.000
M36	0.730	0.029	25.190	0.000
M66	0.463	0.038	12.089	0.000
M93	0.469	0.037	12.814	0.000
M120	0.590	0.038	15.413	0.000
M21	0.102	0.040	2.537	0.011
M39	0.031	0.035	0.875	0.382
M51	0.136	0.038	3.588	0.000
M63	0.341	0.039	8.725	0.000
M108	-0.081	0.026	-3.119	0.002
M114	-0.094	0.029	-3.239	0.001
M12	0.202	0.034	5.874	0.000
M27	-0.173	0.033	-5.165	0.000
M33	0.215	0.033	6.596	0.000
M57	0.183	0.035	5.174	0.000
M69	-0.042	0.035	-1.191	0.234
M90	-0.107	0.028	-3.831	0.000
MGTPAVD BY				
M12	0.479	0.025	19.485	0.000
M27	0.423	0.030	13.866	0.000
M33	0.470	0.027	17.351	0.000
M57	0.399	0.026	15.255	0.000
M69	0.499	0.027	18.388	0.000
M90	0.583	0.023	25.328	0.000
M21	-0.031	0.024	-1.285	0.199
M39	0.163	0.020	8.080	0.000
M51	-0.091	0.024	-3.840	0.000
M63	-0.250	0.023	-10.662	0.000
M108	0.023	0.017	1.324	0.185
M114	0.039	0.020	1.953	0.051
M6	-0.090	0.025	-3.594	0.000
M24	0.102	0.021	4.912	0.000
M36	-0.063	0.024	-2.673	0.008
M66	0.124	0.023	5.439	0.000

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    M93              0.057      0.025      2.281      0.023
    M120             0.134      0.023      5.925      0.000
 MCOMP    BY
    M45              0.545      0.025     21.750      0.000
    M102             0.727      0.017     43.514      0.000
    M111             0.620      0.022     28.128      0.000
    M126             0.661      0.020     32.345      0.000
    M9               0.072      0.029      2.449      0.014
    M87             -0.053      0.024     -2.171      0.030
    M96             -0.079      0.019     -4.125      0.000
    M117             0.448      0.030     15.068      0.000
 MCOOP    BY
    M9               0.400      0.034     11.916      0.000
    M87              0.722      0.036     20.331      0.000
    M96              0.849      0.034     25.187      0.000
    M117             0.186      0.034      5.471      0.000
    M45              0.077      0.027      2.836      0.005
    M102             0.038      0.019      1.945      0.052
    M111             0.079      0.024      3.289      0.001
    M126            -0.037      0.023     -1.583      0.113
 MSEFF    WITH
    MSC              0.887      0.024     37.631      0.000
 MINT     WITH
    MSC              0.859      0.023     37.505      0.000
    MSEFF            0.849      0.020     41.583      0.000
 MIMPT    WITH
    MSC              0.359      0.039      9.284      0.000
    MSEFF            0.447      0.041     10.869      0.000
    MINT             0.489      0.039     12.594      0.000
 MUSE     WITH
    MSC              0.387      0.033     11.662      0.000
    MSEFF            0.470      0.034     13.720      0.000
    MINT             0.560      0.035     16.044      0.000
    MIMPT            0.776      0.055     14.178      0.000
 MMNDSETF WITH
    MSC             -0.406      0.045     -9.027      0.000
    MSEFF           -0.430      0.042    -10.332      0.000
    MINT            -0.419      0.042    -10.042      0.000
    MIMPT           -0.072      0.043     -1.702      0.089
    MUSE            -0.144      0.041     -3.514      0.000
 PERSISTE WITH
    MSC              0.454      0.027     16.618      0.000
    MSEFF            0.519      0.027     19.528      0.000
    MINT             0.532      0.027     19.829      0.000
    MIMPT            0.563      0.037     15.235      0.000
    MUSE             0.580      0.030     19.458      0.000
    MMNDSETF        -0.220      0.037     -5.955      0.000
 MLPCNTRS WITH
    MSC              0.390      0.063      6.206      0.000
    MSEFF            0.471      0.053      8.928      0.000
    MINT             0.477      0.050      9.545      0.000
    MIMPT            0.395      0.089      4.423      0.000
    MUSE             0.503      0.068      7.401      0.000
    MMNDSETF        -0.107      0.077     -1.400      0.162
    PERSISTENC       0.634      0.081      7.865      0.000
 MLPDEEP  WITH
    MSC              0.512      0.037     13.941      0.000
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MSEFF	0.568	0.031	18.159	0.000
MINT	0.544	0.032	17.050	0.000
MIMPT	0.416	0.053	7.836	0.000
MUSE	0.493	0.042	11.645	0.000
MMNDSETF	-0.164	0.052	-3.134	0.002
PERSISTENC	0.708	0.045	15.664	0.000
MLPCNTRSTR	0.733	0.048	15.227	0.000
MLPMEMOR WITH				
MSC	0.271	0.033	8.212	0.000
MSEFF	0.329	0.033	10.020	0.000
MINT	0.328	0.033	10.098	0.000
MIMPT	0.276	0.034	8.219	0.000
MUSE	0.356	0.031	11.470	0.000
MMNDSETF	-0.010	0.040	-0.260	0.795
PERSISTENC	0.487	0.031	15.776	0.000
MLPCNTRSTR	0.474	0.037	12.743	0.000
MLPDEEP	0.593	0.034	17.218	0.000
MGTMAST WITH				
MSC	0.440	0.031	14.259	0.000
MSEFF	0.571	0.027	21.441	0.000
MINT	0.624	0.027	22.926	0.000
MIMPT	0.814	0.031	26.002	0.000
MUSE	0.823	0.022	37.173	0.000
MMNDSETF	-0.192	0.038	-5.064	0.000
PERSISTENC	0.753	0.024	30.940	0.000
MLPCNTRSTR	0.586	0.090	6.525	0.000
MLPDEEP	0.568	0.046	12.407	0.000
MLPMEMORY	0.354	0.029	12.145	0.000
MGTPAPP WITH				
MSC	0.666	0.025	26.976	0.000
MSEFF	0.678	0.024	28.483	0.000
MINT	0.644	0.026	24.473	0.000
MIMPT	0.709	0.033	21.252	0.000
MUSE	0.501	0.030	16.502	0.000
MMNDSETF	-0.178	0.041	-4.369	0.000
PERSISTENC	0.495	0.026	19.003	0.000
MLPCNTRSTR	0.456	0.040	11.405	0.000
MLPDEEP	0.520	0.028	18.842	0.000
MLPMEMORY	0.368	0.031	11.908	0.000
MGTMAST	0.633	0.024	26.503	0.000
MGTPAVD WITH				
MSC	-0.464	0.033	-14.095	0.000
MSEFF	-0.366	0.035	-10.534	0.000
MINT	-0.345	0.035	-9.783	0.000
MIMPT	0.321	0.036	8.959	0.000
MUSE	0.149	0.036	4.086	0.000
MMNDSETF	0.626	0.044	14.281	0.000
PERSISTENC	0.064	0.035	1.799	0.072
MLPCNTRSTR	0.027	0.057	0.481	0.631
MLPDEEP	-0.048	0.043	-1.112	0.266
MLPMEMORY	0.168	0.037	4.572	0.000
MGTMAST	0.198	0.031	6.413	0.000
MGTPAPP	0.081	0.029	2.812	0.005
MCOMP WITH				
MSC	0.655	0.026	25.217	0.000
MSEFF	0.752	0.022	34.282	0.000
MINT	0.665	0.026	25.207	0.000

MIMPT	0.741	0.036	20.530	0.000
MUSE	0.696	0.029	23.986	0.000
MMNDSETF	-0.227	0.042	-5.448	0.000
PERSISTENC	0.660	0.025	26.505	0.000
MLPCNTRSTR	0.553	0.036	15.283	0.000
MLPDEEP	0.629	0.025	24.866	0.000
MLPMEMORY	0.411	0.030	13.556	0.000
MGTMAST	0.819	0.020	40.132	0.000
MGTPAPP	0.938	0.016	60.285	0.000
MGTPAVD	0.073	0.036	2.012	0.044
MCOOP WITH				
MSC	0.223	0.037	5.969	0.000
MSEFF	0.316	0.036	8.777	0.000
MINT	0.318	0.036	8.710	0.000
MIMPT	0.346	0.038	9.023	0.000
MUSE	0.431	0.036	12.064	0.000
MMNDSETF	-0.055	0.041	-1.335	0.182
PERSISTENC	0.342	0.031	11.201	0.000
MLPCNTRSTR	0.354	0.039	9.074	0.000
MLPDEEP	0.389	0.033	11.730	0.000
MLPMEMORY	0.333	0.031	10.805	0.000
MGTMAST	0.447	0.030	14.673	0.000
MGTPAPP	0.350	0.034	10.256	0.000
MGTPAVD	0.208	0.039	5.294	0.000
MCOMP	0.437	0.030	14.577	0.000
Intercepts				
M18	2.590	0.043	59.872	0.000
M75	2.833	0.049	58.280	0.000
M84	2.764	0.046	59.707	0.000
M30	2.675	0.045	59.944	0.000
M60	2.989	0.053	56.663	0.000
M105	3.085	0.056	55.378	0.000
M123	2.955	0.053	55.634	0.000
M3	3.116	0.055	56.329	0.000
M81	2.823	0.051	55.317	0.000
M48	3.900	0.087	44.936	0.000
M78	4.465	0.114	39.172	0.000
M54	4.097	0.095	43.337	0.000
M99	4.124	0.096	42.896	0.000
M15	2.128	0.030	70.156	0.000
M42	2.511	0.040	62.919	0.000
M72	2.460	0.040	61.895	0.000
S12	4.049	0.092	43.929	0.000
S21	3.564	0.072	49.388	0.000
S36	3.609	0.068	52.808	0.000
S51	4.076	0.100	40.952	0.000
S6	2.788	0.048	58.161	0.000
S24	2.682	0.042	63.448	0.000
S33	3.461	0.066	52.802	0.000
S42	3.067	0.056	54.582	0.000
S48	2.634	0.043	60.643	0.000
S15	2.918	0.052	56.530	0.000
S30	2.697	0.044	60.628	0.000
S39	3.128	0.056	55.405	0.000
S45	2.919	0.049	58.995	0.000
S3	2.791	0.046	61.017	0.000
S9	2.279	0.034	67.477	0.000

S18	2.277	0.033	69.307	0.000
S27	2.326	0.035	66.301	0.000
M21	4.221	0.105	40.034	0.000
M39	5.053	0.146	34.636	0.000
M51	3.703	0.081	45.635	0.000
M63	3.442	0.070	49.302	0.000
M108	4.769	0.122	38.988	0.000
M114	4.910	0.128	38.396	0.000
M6	2.840	0.050	56.480	0.000
M24	3.314	0.066	49.888	0.000
M36	2.679	0.044	61.042	0.000
M66	4.112	0.100	41.152	0.000
M93	3.150	0.064	49.512	0.000
M120	3.148	0.058	54.534	0.000
M12	2.677	0.050	53.768	0.000
M27	2.456	0.043	57.057	0.000
M33	3.126	0.063	49.939	0.000
M57	1.880	0.025	73.802	0.000
M69	2.631	0.050	52.422	0.000
M90	3.045	0.064	47.495	0.000
M45	3.209	0.063	50.950	0.000
M102	3.636	0.074	49.284	0.000
M111	3.548	0.070	50.736	0.000
M126	3.457	0.072	47.832	0.000
M9	3.087	0.060	51.227	0.000
M87	2.838	0.053	53.328	0.000
M96	3.111	0.060	51.437	0.000
M117	3.272	0.064	50.911	0.000
Variances				
MSC	1.000	0.000	999.000	999.000
MSEFF	1.000	0.000	999.000	999.000
MINT	1.000	0.000	999.000	999.000
MIMPT	1.000	0.000	999.000	999.000
MUSE	1.000	0.000	999.000	999.000
MMNDSETF	1.000	0.000	999.000	999.000
PERSISTENC	1.000	0.000	999.000	999.000
MLPCNTRSTR	1.000	0.000	999.000	999.000
MLPDEEP	1.000	0.000	999.000	999.000
MLPMEMORY	1.000	0.000	999.000	999.000
MGTMAST	1.000	0.000	999.000	999.000
MGTPAPP	1.000	0.000	999.000	999.000
MGTPAVD	1.000	0.000	999.000	999.000
MCOMP	1.000	0.000	999.000	999.000
MCOOP	1.000	0.000	999.000	999.000
Residual Variances				
M18	0.366	0.043	8.572	0.000
M75	0.396	0.020	19.722	0.000
M84	0.291	0.026	11.182	0.000
M30	0.690	0.028	24.873	0.000
M60	0.416	0.027	15.171	0.000
M105	0.364	0.024	15.019	0.000
M123	0.385	0.020	19.614	0.000
M3	0.351	0.025	13.777	0.000
M81	0.497	0.025	20.173	0.000
M48	0.473	0.026	17.976	0.000
M78	0.429	0.034	12.519	0.000
M54	0.413	0.035	11.727	0.000

M99	0.410	0.058	7.129	0.000
M15	0.489	0.059	8.227	0.000
M42	0.738	0.034	21.761	0.000
M72	1.000	0.000	3588.906	0.000
S12	0.268	0.043	6.229	0.000
S21	0.432	0.023	18.537	0.000
S36	0.371	0.031	12.045	0.000
S51	0.404	0.029	14.102	0.000
S6	0.634	0.021	29.962	0.000
S24	0.527	0.024	21.589	0.000
S33	0.443	0.093	4.777	0.000
S42	0.545	0.024	22.350	0.000
S48	0.568	0.044	12.859	0.000
S15	0.391	0.093	4.210	0.000
S30	0.573	0.023	24.764	0.000
S39	0.412	0.029	14.418	0.000
S45	0.426	0.032	13.462	0.000
S3	0.608	0.031	19.415	0.000
S9	0.505	0.031	16.538	0.000
S18	0.397	0.031	12.872	0.000
S27	0.453	0.033	13.613	0.000
M21	0.672	0.027	24.551	0.000
M39	0.631	0.032	19.936	0.000
M51	0.679	0.024	28.139	0.000
M63	0.539	0.021	25.305	0.000
M108	0.427	0.029	14.876	0.000
M114	0.442	0.029	15.264	0.000
M6	0.603	0.023	25.843	0.000
M24	0.527	0.024	21.703	0.000
M36	0.525	0.024	21.745	0.000
M66	0.581	0.025	23.198	0.000
M93	0.611	0.023	26.124	0.000
M120	0.540	0.025	21.850	0.000
M12	0.729	0.023	31.131	0.000
M27	0.801	0.026	31.027	0.000
M33	0.667	0.025	26.371	0.000
M57	0.833	0.021	39.125	0.000
M69	0.757	0.026	28.817	0.000
M90	0.637	0.026	24.260	0.000
M45	0.660	0.023	28.468	0.000
M102	0.445	0.022	20.496	0.000
M111	0.567	0.024	23.659	0.000
M126	0.583	0.023	25.356	0.000
M9	0.810	0.023	35.520	0.000
M87	0.509	0.041	12.277	0.000
M96	0.332	0.049	6.761	0.000
M117	0.692	0.023	30.151	0.000

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
M18	0.634	0.043	14.833	0.000
M75	0.604	0.020	30.079	0.000
M84	0.709	0.026	27.303	0.000
M30	0.310	0.028	11.171	0.000
M60	0.584	0.027	21.255	0.000
M105	0.636	0.024	26.227	0.000

M123	0.615	0.020	31.276	0.000
M3	0.649	0.025	25.441	0.000
M81	0.503	0.025	20.416	0.000
M48	0.527	0.026	20.061	0.000
M78	0.571	0.034	16.683	0.000
M54	0.587	0.035	16.663	0.000
M99	0.590	0.058	10.262	0.000
M15	0.511	0.059	8.605	0.000
M42	0.262	0.034	7.727	0.000
M72	0.000	0.000	0.034	0.973
S12	0.732	0.043	17.024	0.000
S21	0.568	0.023	24.357	0.000
S36	0.629	0.031	20.449	0.000
S51	0.596	0.029	20.807	0.000
S6	0.366	0.021	17.326	0.000
S24	0.473	0.024	19.363	0.000
S33	0.557	0.093	6.013	0.000
S42	0.455	0.024	18.647	0.000
S48	0.432	0.044	9.790	0.000
S15	0.609	0.093	6.565	0.000
S30	0.427	0.023	18.481	0.000
S39	0.588	0.029	20.560	0.000
S45	0.574	0.032	18.106	0.000
S3	0.392	0.031	12.521	0.000
S9	0.495	0.031	16.227	0.000
S18	0.603	0.031	19.580	0.000
S27	0.547	0.033	16.414	0.000
M21	0.328	0.027	11.991	0.000
M39	0.369	0.032	11.658	0.000
M51	0.321	0.024	13.323	0.000
M63	0.461	0.021	21.666	0.000
M108	0.573	0.029	19.958	0.000
M114	0.558	0.029	19.247	0.000
M6	0.397	0.023	17.030	0.000
M24	0.473	0.024	19.517	0.000
M36	0.475	0.024	19.697	0.000
M66	0.419	0.025	16.762	0.000
M93	0.389	0.023	16.658	0.000
M120	0.460	0.025	18.615	0.000
M12	0.271	0.023	11.579	0.000
M27	0.199	0.026	7.718	0.000
M33	0.333	0.025	13.179	0.000
M57	0.167	0.021	7.824	0.000
M69	0.243	0.026	9.260	0.000
M90	0.363	0.026	13.851	0.000
M45	0.340	0.023	14.643	0.000
M102	0.555	0.022	25.528	0.000
M111	0.433	0.024	18.100	0.000
M126	0.417	0.023	18.145	0.000
M9	0.190	0.023	8.344	0.000
M87	0.491	0.041	11.835	0.000
M96	0.668	0.049	13.606	0.000
M117	0.308	0.023	13.419	0.000

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