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Math Skill Growth and Learning Differences in Higher Education. Can Lower-Skilled Students Catch up?

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Math skill growth and learning differences in higher education. Can lower-skilled students catch up?

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Studies determining students' success in higher education mostly rely on students' predetermined baseline variables like high school GPA or ACT scores and, therefore, describe skill differences at the beginning of college but not the development of these differences over time. Whether ex-ante lower-skilled students can catch up or higher-skilled students may expand their initial lead remains unclear. We investigate the students' learning growth in a business math course and analyze if the gap between initially higher and lower-skilled students changes. Also, we provide possible reasons for different skill growth rates using panel data and mixed-effects models. The results suggest that ex-ante higher-skilled students become disproportionately better (cumulative learning pattern). However, we find evidence that this is only because of engagement effects. In other words, ex-ante lower-skilled students cannot catch up and fall behind even more because they seem less engaged in their studies than higher-skilled students.

Keywords: math skill; learning growth; higher education; learning differences; student heterogeneity

1. Introduction

Policy decisions often focus on outcomes after students arrive at higher education institutes (Stinebrickner & Stinebrickner 2008). However, most studies investigating students' college outcomes use background and personal characteristics that influence students' skills before college entrance, e. g. high school GPA (Grade Point Average) and SAT (Scholastic Assessment Test) or ACT (American College Test) scores (see section 2.2). This view is problematic insofar as, on the one hand, these entrance qualifications are clear indications for college GPAs and dropout probabilities. On the other hand, these variables measure differences at the beginning of the student's college learning process. Studies measuring college success based on students' background characteristics mostly ignore the possibility for individual skill development over time in college. For instance, it is well known that a higher prior GPA leads to a higher college GPA; however, with this information, one can only conclude that students with a prior GPA might gain, on average, a higher college GPA. It remains unclear whether lower-skilled students can catch up (a little) or higher-skilled students may expand their initial lead.

Only a few studies focus on the development and growth pattern of academic achievement, and none investigates students in higher education. Bodovski & Farkas (2007), for instance, present evidence for early elementary schools that students who show poor mathematical performance initially achieve the lowest skill growth, a hint for an increasing gap over time. The same was found in reverse. Kikas et al. (2009) obtained similar results in their study based on primary school students. In higher education, studies focus either on students' background information or motivational and engagement factors (see section 2.3). Therefore, our study tries to fill this gap and focus on students' initial and learning differences in math over the first semester. We investigate the students' learning growth in math and analyze not only if the gap between initially higher and lower-skilled students changes but also provide possible reasons for these different skill growth rates.

2. State of the art

2.1 Theoretical concepts of academic performance and skill growth

Various theoretical concepts have been developed in the last decades to explain academic performance and skill growth in different perspectives of educational research. There are, among others, education product functions (e. g. Brewer 2010), supply-usage models (e. g. Brühwiler & Blatchford 2011), models focusing on motivational and engagement factors (e. g. Kahu 2013; Kahu & Nelson 2018), and skill growth patterns (e. g. Stanovich 1986; Little et al. 2020)

The most common approach for predicting academic performance is an education product function (EPF). The concept, adapted from economic product functions (e. g., Cobb-Douglas functions), is quite simple. By gathering students' individual and institutional factors determining academic performance as dependent variables, these models predict educational outcome as the independent variable (see e. g. Park et al. 1990; Mallik & Shankar 2016).

A supply usage model takes different supply characteristics, such as teacher competency or classroom context (e. g., class size, class heterogeneity) as well as institutional factors (e. g., educational system, school) and the students' usage characteristics (learning environments, individual preconditions, individual learning processes) into account. Therefore, it describes the supply and the usage of learning opportunities, as well as mediating effects with further concerning variables in the context of learning outcomes. Students' motivation and engagement are performance-related characteristics that could be implemented into EPFs or supply-usage models. However, these topics are theoretically complex and empirical research mainly investigates these characteristics separately (see e. g. Kuh et al. 2008, Stienebrickner & Stinebrickner 2008, Büchele 2021).

This study mainly focuses on students' learning and individual skill growth. Recently, Little et al. (2020) summarized the existing theoretical framework and three models of skill growth are of interest: 1) a cumulative model, where ex-ante higher skills result in an even higher skill growth rate; 2) a compensatory model, where ex-ante lower-skilled students catch up and show a higher skill-growth compared to initial higher-skilled students; and 3) a stable model where skill differences between students stay constant over time. However, the cumulative model of skill growth is the most accepted one regarding the "Matthew effect "(Stanovich 1986), arguing that students with higher initial skills can additionally benefit during the learning process. This idea is in line with a self-reinforcing effect of interest, self-efficacy, and learning outcome (for mathematics), as described by Ma (1997).

Empirically, however, the situation seems not so clear. Firstly, studies find evidence for both cumulative and compensating skill growth in reading (Pfost et al. 2014) and math (Bodovsko & Farkas 2007; Salaschek et al. 2014; Kikas 2009). Secondly, these studies primarily focus on skill development during elementary school or (early) high school (Murayama et al. 2013), and the development of math skills is underinvestigated in contrast to reading skill growth (Little et al. 2020). Consequently, there is hardly any empirical evidence on math skill growth patterns in later secondary or tertiary education. Only a few studies affect this topic in the higher education context. For instance, Krohn & O'Connor (2005) find that students with a higher midterm score reduce their learning hours, which could indicate compensating skill growth. On the other hand, Vulperhorst et al. (2018) find some evidence of cumulative skill growth in higher education.

Although various studies investigate determinants of academic performance or dropout in higher education on an EPF basis (see section 2.2), these studies typically describe initial differences but not the development of these differences over time. We can assume that a fully compensating skill growth pattern is unlikely because we would not expect a different college outcome from initial higher or lower-skilled students. Although these background variables cannot fully explain skill growth patterns, they are essential in defining ex-ante lower and higher skilled students and describing the students' heterogeneity.

2.2 Determinants of study success and math achievement

Existing studies analyzed various factors that affect students' general or task-specific performance. High school GPA is a significant determinant of study success (e.g., Anderson et al. 1994, Wolniak & Engberg 2010, Orlov & Roufagalas 2012). Danilowicz-Gösele et al. (2017) specified this correlation and found that a higher final school grade is associated with higher university grades and a higher probability of graduating. Also, university entrance exam grades were linked to students' performance (Park & Kerr 1990, Orlov & Roufagalas 2012). Another determinant influencing study success positively is a higher degree of university experience (Orlov & Roufagalas 2012). This is in line with the finding of Clark & Lovric (2008), who claim that the transition from school to university is a stressful and critical phase of life that can lead to problems during the first time at university. Betts & Morell (1999) pointed out that the type of the former schools and the experience of their teachers are also determinants of students' performance.

In addition, one can observe that typically female students achieve higher grades at the end of their first university years compared to male students (Betts & Morell 1999, Wolniak & Engberg 2010). However, there is some evidence of a reversed gender gap, particularly in math (Behrendt et al. 2015). The family's socioeconomic status (SES) is also considered to influence study success (Sothan 2019). So, Wolniak & Engberg (2010) showed that students of families with lower incomes tend to have lower average grades during the first university year. Betts & Morell (1999) determined that ethnicity also affects students' performance. Furthermore, good language skills positively influence study success (Sothan 2019).

Mallik & Shankar (2016) took a particular look at studies of economic sciences and showed that prior knowledge in economics and higher mathematical skills are correlated to higher performance. These findings are consistent with the results of Anderson et al. (1994). They found that background knowledge in calculus is associated with higher study success in economic sciences.

Besides the presented studies that investigate study success in common, there are also studies focusing on mathematical skill development in higher education. Laging & Voßkamp (2017) expose the degree of mathematical knowledge obtained at secondary schools as a crucial factor. This is associated with the type of school graduating and a student's knowledge background, which also affects mathematical skill development at university. These relations are decisive factors for our study because of the growing heterogeneity in student groups today. Since universities widened access, students' characteristics and previous knowledge became more varied, accompanying lower completion rates (Kahu & Nelson 2018). Mainly, the proportion of students possessing inferior mathematical basic knowledge is growing (Faulkner et al. 2014). Furthermore, the final school grade, particularly the math grade in school and, thereby, the math achievement at school, are central determinants (Cappellari et al. 2012, Faulkner et al. 2014, Laging & Voßkamp 2017).

Determinants concerning personality characteristics and expertise also predict study success. Intelligence is associated with study success (Park & Kerr 1990). Orlov & Roufagalas (2012) point out that a higher level of cognitive reflection leads to higher academic achievements. The same applies to students' ability to use higher-level skills like interpreting and applying available knowledge and creating new knowledge. Robbins et al. (2004) state that academic-related skills predict students' performance and retention. These skills describe cognitive, behavioral, and affective abilities required for solving problems in an academic context. The five factors of personality, which are neuroticism, extroversion, openness, conscientiousness, and agreeableness, affect study success as well (Ackerman et al. 1995). In this regard, conscientiousness is highlighted by Richardson et al. (2012).

These mentioned and often used determinants for predicting academic achievement are ex-ante factors. In this context, Smith (2016) shows that entry grades rather than social characteristics may most strongly influence eventual academic success once students overcome barriers to university admission. On this occasion, aspects being relevant during studies, like motivation and engagement, remain unconsidered. So, in the next section (2.3), we point out the link between student engagement and academic performance since "human capital accumulation is far from predetermined at the time of college entrance" (Stinebrickner & Stinebrickner 2008, p.44).

2.3 Student engagement and academic achievement

Study effort is an important determinant of students' performance (Park & Kerr 1990, Sothan 2019). According to Stinebrickner & Stinebrickner (2008), it is even one of the essential factors predicting study success. The authors even state that an increase in study effort may improve skill development regardless of other determinants. A further crucial and more global factor determining study effort is the degree of engagement students show (Kuh et al. 2008). This, however, is influenced by motivational aspects (Kahu & Nelson 2018). So, higher motivation can lead to higher engagement, accompanied by increased study effort, which may result in improved academic achievements.

From the point of view of students and lecturers, motivational factors also attach importance when explaining study success. Killen (1994) presents results revealing that both groups assess interest in the learning object, consistent effort, self-discipline, the desire to learn, and the ability to work independently, which affects students' motivation to belong to the main determinants of students' performance. Laging & Voßkamp

(2017) confirm this correlation. They also found motivational aspects to be factors influencing math performance significantly, including math self-efficacy, the math self-concept of a student, math interest, mastery goal orientation, math anxiety, and the individual perceived value of mathematics. The learning goal orientation also positively influences motivation (Richardson et al. 2012). According to Ackerman et al. (1995), self-estimates of ability, students' self-concept, motivational skills, and task-specific self-efficacy influence positive and negative motivational thoughts that are suggested to be predictors of students' performance. Robbins et al. (2004) emphasize achievement motivation as one of the main predictors of grades at university. Students' motivation increases the willingness to learn and the desire to keep learning (Chou & Kuo 2012). Thereby higher motivation can increase study success (Romer 1993). Intrinsic motivation affects learning behavior more than extrinsic motivation (Friedman et al. 2001, Richardson et al. 2012). Factors influencing intrinsic motivation are the degree of interest in the learning object, the desire to succeed in studies, students' wish to prove themselves, the attitude towards the lecturer, the presentation of learning materials, and the degree of encouragement by the docent (Kottasz 2005).

The degree of interest in a learning object and students' motivation are determinants of class attendance (Wadesango & Machingambi 2011). Many studies point out a positive but mostly weak correlation between attendance and study success (see e. g. Romer 1993, Devadoss & Foltz 1996, Wadesango & Machingambi 2011, Chou & Kuo 2012, Sothan 2019). However, courses with more mathematical content have lower absenteeism rates (Romer 1993). But a high attendance rate does not necessarily lead to improved academic achievements. Büchele (2021), for instance, highlights the role of behavioral engagement, which is much more important for study success than attendance.

This finding is confirmed by Kahu & Nelson (2018), who show that student engagement has an essential impact on study success and retention. Robinson & Mueller (2014) point out that individual and behavioral engagement foster math achievement. Especially regarding mathematical performance Bodovski & Farkas (2007) present evidence for the high relevance of student engagement. In the context of early elementary school, they show that students demonstrating the lowest performance in the beginning engagement have the most considerable effect on skill development. Carini et al. (2006) found similar correlations in the context of higher education. They also state that student engagement is an essential predictor of students' performance and personal development. Student engagement is, for example, shown by a student's course load. In this respect, it may be surprising that taking a full course load has no negative impact but even a little positive impact on study success (Huntington-Klein & Gill 2021). Furthermore, Cappellari et al. (2012) provide evidence that students who wait longer to take an exam tend to obtain lower grades which may be explained by lower student engagement.

Another component affecting study success is academic self-efficacy (Richardson et al. 2012, Sothan 2019). Self-efficacy was found to be positively linked with cognitive and metacognitive strategy use. And appropriate use of learning strategies can improve academic achievements (Roick & Ringeisen 2018).

This section shows that students' ex-ante characteristics (like prior GPA) cannot solely explain students' success and achievement in higher education. Engagement factors also occur during the study and influence students' skill development and academic achievement. Therefore, this paper examines the link between students' pre-existing characteristics and students' engagement factors in the context of predetermined math skills as well as math skill growth.

3. Sample, variables, and descriptive statistics

3.1 Sample and instruments

Data was gathered during an introductory math course for economics at a mid-sized German university in various winter semesters between 2011 and 2019. Altogether, 1,070 students took a math skill test and an accompanying questionnaire at two points, once in the first lecture and again in the middle of the semester after 9 to 10 weeks. The data was raised entirely anonymously, and students knew the gathered data would be used for research studies. The skill tests and questionnaires remain the same over time. Both skill tests consist of 30 tasks, and students could score 30 points (one point per task). The skill tests allow us to analyze students' skill growth in general and more than one particular math topic. Both tests mainly consist of tasks of secondary math education (e. g., arithmetic, algebra, functions, and calculus) with different core competencies (e. g., mathematical modeling competency). Some examples of tasks are solving a double fraction $\frac{3}{8} \cdot \frac{16}{5} / \frac{4}{5}$, a quadratic equation $(x-2)^2 - 2 = -1$, or to determine logarithms like $\log_3 \frac{1}{9}$. A further task, for instance, asked students to explain how the graph of $f(x) = (x-a)^2 + b$ with $a, b \in \mathbb{R}^+$ changes if a is increasing. The tasks in both tests differ but are of comparable difficulty (Laging & Voßkamp 2017). Although both tests only cover secondary math topics, they are mainly designed for the math lecture for economics at the examined university. Since the course as well primarily revises math topics of secondary math schooling in the first weeks of the semester, the tests are closely related to the course, and they can be considered valid assessments for the student's math skill growth in this sample. Within the questionnaires, we raised data on educational, biographical, and affective variables, typical determinants of study success (see sections 2.2 and 2.3). Additionally, we gathered information on students' learning and engagement during the semester. Furthermore, it is essential to mention that the lecturer and course structure remained the same over time.

3.3 Variables

As mentioned above, we gathered additional information from two questionnaires, one at the beginning and the middle of the semester. Table 1 gives an overview of the given variables and means.

[Table 1 near here]

The higher education system in Germany is quite liberal, and students have various freedoms in planning their studies. Therefore, the variables might need further explanations as determinants of math skills. First, we gathered information on the students' math skills through the standardized skill tests at the semester's beginning (T1) and the middle (T2). Comparing the two points, one can see students' skill development from 8.41 points at T1 to 12.06 points at T2. Variable B1 checks for the student's gender. 49 % of the sample are females. Students were engaged in taking a developmental math course (variable B2), which was held before the semester. This so-called "preparatory course "is a two-week summer-school equivalent, revising secondary school math topics. Participation was entirely voluntary, and 60% of the sample took part. However, we do not have information on the attendance rates. Variable B3 checks whether a student already took the credit-bearing introductory math course in a previous semester but did not take or pass the final exam, affecting 13% of the sample. Students can enroll with two different school degrees (variable B4); a regular and a time-shortened degree with lower educational value. This distinction is necessary since, firstly, the access to higher education has been widened, not only in

Germany. Secondly, studies (e. g. Faulkner et al. 2014, Behrendt et al. 2015; Laging & Voßkamp 2017) show that students' math performance is worse when enrolling with time shortened or unregular (e. g. through work experience) degrees, which affects 34 % of the sample. Variable B5 measures a student's secondary school GPA, and variable B6 measures the average math grade in secondary school. The education gap (variable B7) measures the time between the secondary school degree and the beginning of the study. Therefore this variable is also a proxy for students' age. Information on two important affective variables (math interest (A1) and math anxiety (A2)) was raised by psychological scales (see Laging & Voßkamp 2017 for more information). The midterm questionnaire completes the dataset with time-dependent learning variables, which are used as proxy variables for students' learning and engagement during the semester. We gathered the lecture (L1) and tutorial attendance (L2) information on a scale from 1 (never attended) to 6 (always attended). Information on students' persistence (L3) and regularity of learning (L4) was also measured via psychological scales (see Laging & Voßkamp 2017). All the scales have at least good reliability (Cronbach's alpha > .80) and are proven in different studies (e. g. Laging & Voßkamp 2017).

4. Model

Descriptive analysis and results are generally easily biased by further circumstances. Particularly in this sample, for instance, the voluntary remedial course participants (B2) and students retaking the introductory math lecture (B3) are expected to perform significantly better in the first skill test. However, the related advantages in the first skill tests are proven to be compensated over the semester (Büchele 2020a), which affects the learning growth pattern. The same occurs for students retaking the math course since they are expected to have more knowledge in the first skill test but might not show the same learning curve as first-year students when revising the study material a second time. Consequently, we cannot trust the descriptive analysis and need a closer look at the skill growth by analyzing the given determinants of math skills separately and over time.

To investigate the isolated math skill growth, we build a linear regression model in Stata, isolating the fixed-effects part of a linear mixed model. Murayama et al. (2013) performed a similar technique with four points in time and an exponential function. This study, however, measured the students' math skills only at two points. Therefore, we build a linear regression function. Through this particular approach, one can separate the correlations of each variable with the student's math skill for the first and second skill test.

$$Y_{1j} = constant + \sum_{k=1}^{7} \beta_{k1j} B_{k1j} + \sum_{l=1}^{2} \gamma_{l1j} A_{l1j} + \varepsilon_{1j} \quad (1)$$

$$Y_{ij} = constant + time\ dummy + \sum_{k=1}^{7} \beta_{k1j} B_{k1j} + \sum_{l=1}^{2} \gamma_{l1j} A_{l1j} + \sum_{k=1}^{7} \delta_{kij} B_{kij} xTime + \sum_{l=1}^{2} \mu_{lij} A_{lij} xTime + \varepsilon_{ij} \quad (2)$$

$$Y_{ij} = constant + time\ dummy + \sum_{k=1}^{7} \beta_{k1j} B_{k1j} + \sum_{l=1}^{2} \gamma_{l1j} A_{l1j} + \sum_{k=1}^{7} \delta_{kij} B_{kij} xTime + \sum_{l=1}^{2} \mu_{lij} A_{lij} xTime + \sum_{m=1}^{4} \sigma_{m2j} L_{m2j} + \varepsilon_{ij} \quad (3)$$

One can read the models in three steps. First, we estimate the regression coefficients for the student's background and affective variables' on the math skill at the beginning of the semester. Y_{1j} is the $j's$ student's test score at T1, B_{k1j} is the $k'th$ baseline variable ($k \in \{1, 2, \dots, 7\}$) of the $j's$ student at T1, and A_{l1j} is the $l'th$ affective variable ($l \in \{1, 2\}$) of the $j's$ student at T1. The first model is a standard EPF, regressing given ex-ante variables at the students' math skills at T1. Thus, this model identifies ex-ante determinants of students' math skills.

In the transition to the second model, we include $B_{kij}xTime$ as time-interaction effects, with B_{kij} as the $k'th$ baseline variable ($k \in \{1, 2, \ldots, 7\}$) of the $j's$ student at time i ($i \in \{1, 2\}$), and $Time$ as a time dummy variable coded as zero for $i = 1$ and 1 for $i = 2$. Since we now regress these variables on Y_{ij} (the test score of the $j'th$ student at the $i'th$ time), both time points are included simultaneously. Therefore these interaction effects estímate the correlation between each variable with the second test result only, including the first time point as a baseline. This means the interaction effects estimate the effect of each variable on the skill difference between the first and second skill test and can therefore be interpreted as the skill growth for particular students' baseline characteristics. In other words, the second model uses all variables at T1 as a constant, and the time-interaction effect act like the slope (see also Murayama et al. 2013).

In the third step, we include the (time-dependent) learning and engagement variables that only affect the outcome of the second skill test. These variables control for students' learning habits during the semester. Therefore, L_{m2j} is the $m'th$ ($m \in \{1, 2, 3, 4\}$) learning variable (L) of the $j'th$ student at T2.

5. Results

Table 2 reports the step-by-step regression results. One can find the determinants of test performance (at T1) in column 3, which are extended to the interaction effects (isolated skill growth) in column 4. Column 5 also controls for the further learning variables L1 to L4.

[Table 2 near here]

Firstly, one can identify students' characteristics determining the entry math skill (column 3). We found a gender gap, with females performing about 1.2 points worse than male students. Furthermore, these variables can differentiate higher-skilled from lower-skilled students. More precisely, students that participated in the remedial course or took the introductory math course a second time performed significantly better (about 2.5 and 3 points). Additionally, students with a higher prior GPA (2 points per grade), higher math grade (0.6 points per grade), and students with a regular secondary school degree (3 points) have a significant advantage. Students' interest in math correlates positively, while math anxiety negatively influences students' entry math skills.

In the context of this paper, it seems more important how the students' math skill develops over time and whether these skill characteristics are responsible for the learning growth (column 4). While the baseline variables remain the same, the interaction terms significantly affect the students' skill growth. Remedial course participants show a lower skill growth than non-participants and "lose" one point of their advantage. More importantly, however, are the interaction terms of variables B4 and B5. Students with a regular school degree and a higher prior GPA benefit over time and significantly enlarge the baseline gap by 0.8 points (B4*time) and about one point per grade (B5*time). Although there are no baseline differences, older students (B7) show a higher math skill growth rate. No learning difference, and therefore a constant learning pattern, is reported for the gender and students that take the introductory math course a second time, as well as students with different math interests or different math anxiety.

In the third model (column 5), engagement variables are implemented to control for the student's learning behavior. Due to missing values, the sample is reduced to 963 students (1,926 for both time points). Unsurprisingly, students with higher persistence and learning regularity show significantly higher math skill growth. What is surprising, however, is that the coefficients of the interaction terms become smaller and lose their significance which is discussed in the next section.

6. Discussion

6.1 Discussion of results

At first, we analyzed the student's math skill growth with mean differences for different percentiles of entrance math skills and found a slightly compensating growth pattern. Because of reasons like test structures and biased differences (for instance, the compensating effect of the developmental math course over time), these results do not appear trustworthy for the given study and sample. Therefore, we implemented a regression model that helps control certain variables and can simultaneously identify the determinants of entrancing skill and skill growth.

The first model estimates the determinants of math performance at the beginning of the semester (in T1) only. Although these correlations are not surprising and following the literature (see section 2.2), we can identify ex-ante higher and lower-skilled students. Particularly students with a higher prior GPA and a regular entrance qualification perform better in the first skill test. Furthermore, remedial course takers and students who already took the math lecture a previous semester perform significantly better, confirming the descriptive analysis's problems.

Model 2, therefore, gives a more differentiated look at the student's skill development. We found evidence for a slightly cumulative learning pattern of the students since ex-ante higher-skilled students (as defined via model 1) become even better. Vice versa, students fulfilling risk attributes (like a lower prior GPA or a short-track high school degree) are falling behind even more. However, this stands in contrast to the descriptive results, which can be (partly) explained since we find a compensating effect (negative effect of B2*time) of the remedial course non-takers. Furthermore, older students (education gap) have significantly higher skill growth. Surprisingly, students who already took the math course in a previous semester show similar skill growth as first-year students.

The third model additionally controls for students' engagement during the semester. Particularly, the students' regularity and persistence in learning significantly influence their math skill growth. These are essential factors, and their influence on math skills has already been found in other studies (Laging & Voßkamp 2017, Liebendörfer et al. 2022). Controlling for these variables leads to mediating effects regarding the interaction terms B4*Time and B5*Time, which lose their effect size and significance in the transition to the third model. This means that engagement effects are the (only) reason ex-ante higher-skilled students become disproportionately better. In other words, ex-ante lower-skilled students do not catch up because they seem less engaged in their studies than higher-skilled students. Therefore, the observed cumulative learning pattern in the second model exists not because of higher entrance skills but rather through a higher persistence and engagement of these students. A compensatory engagement effect has been reported by other studies as well; however, these conditional engagement effects of high and low-achievers were not observed (Kuh et al. 2008). Further, motivation and metacognitive strategies influence math skill growth during middle school (Murayama et al. 2013).

6.2 Implications

As indicated by model 3, persistence and regularity are critical factors explaining the difference in skill growth of higher- and lower-skilled students. So, interventions and offers aiming at increasing these determinants may also reduce the determined gap in skill growth. An effective educational practice containing various learning opportunities can increase persistence and regularity. All students, particularly lower-skilled students, benefit from these activities if they are of high quality and match the needs of the student groups they address. Therefore, such offers may counteract the increasing gap in achievement growth (Kuh et al. 2008).

First, peer-learning opportunities like student teaching and learning and working with adult learners are adequate educational activities and are assumed to impact study success (Berthelon et al. 2019). Especially in mathematical studies, peer effects are measurable (Brunello et al. 2010). Heterogeneity can improve skill growth. Lower-skilled students benefit more from peer-learning opportunities than higher-skilled students (Kiss 2013, Griffith & Rask 2014). So, using peer effects may be an opportunity to support lower-ability students' learning achievement. However, students tend to work with other students exhibiting similar characteristics, including abilities (Berthelon et al. 2019). Furthermore, group members often show an equivalent level of effort, determining study success (Pu et al. 2020). Therefore, lecturers should provide learning opportunities encouraging students to interact with each other and arrange for heterogeneous grouping at best. In this way, it gets easier for lower-skilled students to group with higher-skilled students (Berthelon et al. 2019). Nevertheless, implementing valuable peer-learning opportunities is complex because of the large degree of self-organization in higher education.

Because students often have problems with mathematical learning and insufficient prior knowledge, many docents offer voluntary support services to meet students' unique needs and reduce the ability gap between lower- and higher-skilled students. The most common additional offers are tutorials and remedial courses. In contrast to mandatory developmental math courses in the US, which are discussed critically (e. g. Bahr 2008), these various kinds of voluntary support services can help reduce heterogeneity (de Paola & Scoppa 2014, Büchele 2020b). Mainly, lower-skilled students profit from such offers (Jamelske 2009). However, in practice, there is generally low and irregular participation in these offers. But students who have already failed the exam use these offers more frequently (Laging & Voßkamp 2017). Participants of remedial math courses possess lower prior knowledge in common (Bettinger & Long 2005). As already mentioned, this may be a reason why our descriptive results indicate a compensating effect. Nevertheless, the investigation shows a slightly cumulative effect encouraged by the low usage rate of additional voluntary offers. So, these offers must meet the demands of students.

In recent years new learning technologies have become popular, and their application is expanding. They also can be used as additional offers to support student engagement and ability growth. Online learning opportunities offer several benefits and can be used synchronously and asynchronously. Asynchronous offers are convenient to students and provide flexibility; therefore, they show high compatibility with students' work schedules, which minimizes barriers preventing students from using these offers regularly (Britto & Rush 2013). Learning technologies can also complement attendance teaching, and students even wish to use digital media in classrooms. Through such offers, they can participate in learning environments anonymously. So, for shy students and students questioning the correctness of their answers, it is easier and more convenient to participate (Brown et al. 2014). Especially lower-skilled students gain profit from using those tools and being more active in class because engagement affects their ability growth particularly (Carini et al. 2006).

6.3 Strength and Limitations

In this study, we investigated the math skill growth of economics students during the first weeks of the semester. Studies examining students' achievement in higher education typically focus on determinants of study success and, therefore, describe skill differences but not the development of these differences over time. We did focus on these differences and found out that, firstly, the initial gap between ex-ante lower and higher skilled students becomes even bigger, and secondly, that the students might be self-responsible for these rising differences since mainly students' engagement factors (learning regularly, persistence, attending classes) are determinants for the risen performance. This study has shown that the (math) skill growth in higher education depends on both students' initial skill and engagement, underlining the theoretical concepts of the Matthew effect (Stanovich 1986) and the self-reinforcing skill effect (Ma 1997).

Some limitations must be pointed out. Firstly, even though we used time-series data and controlled for various performance-related variables, we cannot state that our results are causally interpretable because of possible endogeneity bias. This is mainly because there still might be crucial variables missing that we did or could not raise within the study design. For instance, the student's socioeconomic status (SES) influences academic achievement (Sothan 2019, Wolniak & Engberg 2010). A lower SES results in missing financial support from parents. Therefore, students are more likely to work to make a living, which probably results in fewer learning hours and, thus, less skill growth (Bartolj & Polanec 2018), and persistence (Choi 2018). However, Craft (2019) could not find an influence of SES on the student's first-year achievement. Although low SES students in Germany can use state education financing (Bafög) and might not be as dependent on working, omitting variables cannot be excluded entirely in our model.

Secondly, the external validity of the results is limited. On the one hand, data was raised in one math course for economics at one German university over various years. On the other hand, panel mortality restricts the sample since we only included students from which information was available at both points in time. Furthermore, the student's engagement was measured with scales of learning regularity and persistence as well as attendance in lectures and tutorials, which can be seen critically since these are proxy variables rather than theorized engagement constructs.

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Table 1. Variables and descriptive statistics

Code	Variable	Description and coding	Mean / Percentages	SD	CA
Y1	Math skill (T1)	Students' test score in T1 (min = 0; max = 30).	8.41	4.88	
Y2	Math skill (T2)	Students' test score in T2 (min = 0; max = 30).	12.06	5.69	
B1	Gender	Male = 0; Female = 1	49 % female		
B2	Remedial course participation	Variable for whether a student took a voluntary remedial course before the semester. No = 0; Yes = 1	60 % participation		
B3	Math course already taken	Variable for whether a student already took the entry math course in a previous semester. No = 0; Yes = 1	13 % retakers		
B4	Higher education entrance qualification	Variable for curricular preparations. regular = 1; short = 0	66 % regular		

B5	Prior GPA	Measures high school GPA. higher = better excellent = 4; sufficient = 1	2.56	.56	
B6	Math grade in sec. school	Average math grade in high school (higher = better) excellent = 5; non-sufficient = 1	3.49	.88	
B7	Education gap	Measures years between secondary school degree and start of studies.	1.85	2.23	
A1	Math interest	Mean Index (4 Items) From “low” = 1 to “high” = 6	3.56	1.12	.94
A2	Math anxiety	Mean Index (3 Items) From “low” = 1 to “high” = 6	3.87	1.35	.87
L1	Lecture attendance	Scale from “never” = 1 to “all sessions” = 6	5.69	.67	
L2	Tutorial attendance	Scale from “never” = 1 to “all sessions” = 6	5.16	1.47	
L3	Learning persistence	Mean Index (4 Items) From “low” = 1 to “high” = 6	4.85	1.12	.83

L4	Learning regularity	Mean Index (3 Items) From “low” = 1 to “high” = 6	4.08	1.03	.83

Table 2. Regression results of Model (1) to (3)

Code	Variable	Model 1	Model 2	Model 3
		Coefficient (robust SE)	Coefficient (robust SE)	Coefficient (robust SE)
	Constant	-3.92*** (.98)	-3.92*** (.98)	-5.33*** (1.05)
	time dummy		-.36 (1.60)	-3.14 (1.85)
B1	Gender	-1.21*** (.26)	-1.21*** (.26)	-1.24*** (.27)
B2	Remedial course taken	2.41*** (.26)	2.41*** (.26)	2.42*** (.27)
B3	Math course already taken	3.01*** (.40)	3.01*** (.40)	3.01*** (.41)
B4	HE entrance qualification	3.62*** (.26)	3.62*** (.26)	3.69*** (.27)
B5	Prior GPA	1.94*** (.28)	1.94*** (.28)	1.95*** (.28)
B6	Prior math grade (in high school)	.49** (.18)	.49** (.18)	.48** (.18)
B7	Education gap	.07 (.06)	.07 (.06)	.08 (.06)
A1	Math interest	.73*** (.13)	.73*** (.13)	.75*** (.13)
A2	Math anxiety	-.37*** (.11)	-.37*** (.11)	-.38*** (.11)
B1*Time	skill growth according to Gender		-.09 (.39)	-.21 (.40)
B2*Time	skill growth according to		-.98*	-1.17**

	remedial course takers		(.41)	(.42)
B3*Time	skill growth according to math already taken		.04 (.61)	-.78 (.61)
B4*Time	skill growth according to entrance qualification		.83* (.41)	.52 (.42)
B5*Time	skill growth according to prior GPA		1.02* (.43)	.70 (.44)
B6*Time	skill growth according to prior math grade		.16 (.28)	.19 (.28)
B7*Time	skill growth according to the education gap		.21* (.10)	.14 (.10)
A1*Time	skill growth according to math interest		.15 (.19)	-.04 (.20)
A2*Time	skill growth according to math anxiety		.02 (.16)	.12 (.16)
L1	Lecture attendance			-.05 (.23)
L2	Tutorial attendance			.11 (.11)
L3	Persistence			.61*** (.17)
L4	Regularity			.60*** (.16)
Dependent variables		Y1	Y1 (B1 - A2) Y2 (other)	Y1 (B1 - A2) Y2 (other)
N		1,003	2,006	1,926
Adj. R^2		.316	.405	.425

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