Increasing Perseverance in Math:

Evidence from a Field Experiment in Norway*

Eric Bettinger, Stanford University and the NBER

Sten Ludvigsen, University of Oslo

Mari Rege, University of Stavanger

Ingeborg F. Solli, University of Stavanger

David Yeager, University of Texas-Austin

Abstract:

Research by psychologists and economists demonstrates that many non-cognitive skills are malleable in both children and adolescents, but we have limited knowledge on what schools can do to foster these skills. In a real effort field experiment, we investigate how schools can increase students' perseverance in math by shaping students' beliefs in their abilities to learn. Using protocols adapted from psychology, we experimentally manipulate students' beliefs in their ability to learn. Three weeks after our treatment, we find persistent treatment effects on students' perseverance and academic performance in math. These results are strongest among students who, prior to the experiment, had less of a belief in their ability to learn. The findings suggest that a low-cost intervention focused on students' mindset can improve students' engagement and performance.

* Corresponding author: Mari Rege, University of Stavanger, 4036 Stavanger, Norway. E-mail: Mari.rege@uis.no.
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1. Introduction

Non-cognitive skills, such as self-control and perseverance, predict success in education and in labor markets (Borghans et al. 2008, Heckman et al. 2006, Roberts et al. 2007). While researchers are still trying to understand the causal mechanisms, there is irrefutable evidence that individuals with higher non-cognitive skills are more likely to graduate from high school, have higher rates of college attendance and completion, higher wages and better employment, and even better health outcomes (Carneiro et al. 2007, Kautz et al. 2014). Moreover, research by psychologists and economists demonstrates that many non-cognitive skills are malleable in both children and adolescents (Alan et al. 2015, Kautz et al. 2014). Still, however, we have limited knowledge on what schools can do to foster these skills.

In a real effort field experiment, we investigate how schools can increase students' perseverance in math by shaping students' beliefs in their abilities to learn, i.e. in their potential to benefit from effort. We define a student with high perseverance as someone who consistently chooses to exert high effort – she stays focused on challenging tasks, works hard, and does not give up. In a stylized model we assume that the expected marginal benefit of exerting effort is increasing in the student's belief in her abilities to learn. This leads us to hypothesize that increasing a student's belief in her ability to learn leads to increased effort in a learning task.

An extensive literature in psychology has demonstrated that it is possible to shape students' beliefs in their ability to learn, and cause lasting improvements in school outcomes, by teaching students about the brain's potential to grow and change (Aronson et al. 2002, Blackwell et al. 2007, Good et al. 2003, Paunesku et al. 2015, Yeager et al. 2016). In this literature, a student's belief in her abilities to learn has been referred to as "implicit theories of intelligence" (Dweck & Leggett 1988). More recently, after Dweck's popular book *Growth Mindset* (Dweck 2006), it is commonly referred to as her "academic mindset." Students with a "fixed mindset" believe their intelligence or talents are fixed traits. By contrast, students with a "growth mindset" believe that their abilities can be developed through dedication, hard work on challenging tasks, finding the right learning strategies, and seeking assistance from others (Yeager & Dweck 2012).

Our field experiment relies on the web-based mindset intervention in Yeager et al. (2016). We adapted the intervention, which was based in large part on prior work by Aronson et al. (2002) and Paunesku et al. (2015), to the Norwegian language, culture and context. The treatment condition exposes students to growth mindset through online reading and writing exercises. These exercises focus on (1) how intellectual abilities are malleable and accordingly how the brain can grow and change, (2) how to cope with confusion and difficulty, (3) how hard work on challenging exercises improves the neural connections in one's brain, and (4) how personal goals can give purpose and relevance to motivate effort in difficult tasks (Yeager et al. 2014). The control condition has analogous activities, which teach students facts about memory and brain functioning, but does not address the malleability of intellectual ability.

In the spring of 2016, 385 Norwegian high school students participated in the field experiment. During normal school instructional time, we introduced students to a website. Each student logged in individually to the website on personal laptops. Once students logged in, our software randomly assigned them to either the mindset or control conditions. The students worked on the online reading and writing exercises during two sessions of 45 minutes, two weeks apart. In the third session, we gave students a real effort task, designed to capture a familiar school activity, in which perseverance is critical to learn and succeed. Specifically, students received a series of 34 multiple-choice algebra questions sequentially. The algebra questions were extremely challenging, possibly making many students frustrated and ready to give up. We told the students that we would like them to "do their best" and that they "may learn something from working on the math questions." We also explained carefully that students' answers would be kept confidential and that their performance would not affect their grade. As many students did not have time to finish all the questions, or "gave up" – clicking fast through the questions—we look at how many correct questions students had on the first 10, 20 and all 34 questions.

The experimental results demonstrate that treated students have significantly more correct answers on the first ten questions compared to students in the control group (19 percent of the standard deviation), but there is no significant difference between treated and control when looking at the first 20 or all 34 questions. For student who entered the experiment with a pre-existing fixed mindset, the treatment effect is large and significant for all three outcome measures; treated students scored 35, 30 and 29 percent of a standard deviation higher than control students on the first 10, 20 and all 34 questions respectively. For students with a growth mindset pre-treatment, there are no significant treatment effects. Our descriptive statistics demonstrate that prior to the experiment, students with low grade point average (GPA) and students on vocational tracks have less of a growth mindset. Investigating these subsamples we find large and significant treatment effects. Among students in vocational tracks, the treatment increased the score on all 34 questions by 25 percent of a standard deviation. Our results are consistent with the hypothesis that it is possible to increase students' perseverance in math by shaping their beliefs in their abilities to learn, in particular among students who initially had a fixed mindset.

This paper relates to several strands of literature in economics. First, as noted above, our work builds on the emerging literature on non-cognitive skills by investigating whether schools can foster perseverance by shaping their beliefs in their abilities to learn. Second, our work also relates to recent developments in behavioral economics of education (Koch et al. 2015, Lavecchia et al. 2014) which attempt to understand how low-cost behavioral or psychological interventions can help students better utilize the learning opportunities already within the educational system (e.g. Bettinger et al. 2012, Carrell et al. 2016, Castleman & Page 2015). We contribute to this literature by investigating how a brief, low-cost, psychological intervention can lead students to increase their effort in a learning task three weeks later. Third, our mindset experiment builds on other behavioral economics experiments designed to understand individual's motivation and performance in real effort choices in the lab or field (e.g. Azmat & Iriberri 2010, Bradler et al. 2016, Eriksson et al. 2009, Koch et al. 2015, Kvaløy et al. 2015).

Finally, our experiment contributes to the psychological literature on mindset. As argued by Wilson and Buttrick (2016), despite the convincing randomized controlled trials, the lasting effects of the brief mindset interventions on school outcomes seem "magical" (Yeager & Walton, 2011) because we do not understand the mechanisms through which they affect students' behavior. While the theoretical work on how the mindset interventions affect behavior is well developed (Cohen & Sherman 2014, Walton 2014, Yeager & Walton 2011), the empirical work is not. Several studies use survey questions to investigate how the intervention affects the students' beliefs and strategies (attributions and goals) for future behavior (see e.g. Blackwell et al. 2007, Yeager et al. 2016). However, psychological interventions have not examined the impacts of mindset on everyday academic behaviors over time via real effort tasks. We shine some light into this "black box", by demonstrating that the mindset intervention affects perseverance in a real effort learning task which took place three weeks after the intervention.

2. Background

2.1 Institutional Context

Students start high school in Norway around age 16 after ten years of compulsory schooling similar for everybody (primary and middle school). A student can apply to any high school in her county. When applying a student has to decide whether to enroll in a vocational track, which leads directly to employment, or an academic track, which prepares students to attend college after high school completion. Students rank three desired choices, and acceptance is based on students' GPAs from middle school. All students are guaranteed acceptance into a high school in the county.

Norwegian high schools typically last three to four years depending on the specific program. Only 70 percent of students complete high school within five years. For vocational track students, completion rates are particularly low – only 55 percent complete within five years. While Norwegian policymakers have aimed several reforms at improving high school completion rates, there have been no systematic efforts to alter students' beliefs in their abilities to learn as a means of improving educational outcomes.

2.2 Conceptual Framework

We define a student with high perseverance as someone who consistently exerts high effort – she stays focused on task, works hard on challenging yet potentially rewarding tasks, and does not give up.[1] Below we present a stylized model illustrating how shaping students' beliefs in their abilities to learn can affect their perseverance.

Consider a learning situation. A student chooses how much effort to exert. By staying focused on task, working hard and not giving up, the student can benefit from learning. However, there may be an opportunity cost of exerting high effort – for example, the student cannot check her phone, day dream, or talk to a class mate.

Let $p\mathrm{B}(e)$ represent the student's expected benefit of learning when exerting effort, e, where $B' > 0, B'' < 0$ and p is the student's belief in her abilities to learn, i.e. how effort translate into benefit of learning. Let $\mathrm{C}(e)$ represent the opportunity cost of exerting effort, where $C' > 0$ and $C'' > 0$. A utility maximizing student chooses effort level e^* such that $\mathrm{C}'(e^*) = \mathrm{p} \cdot \mathrm{B}'(e^*)$. From this first order condition, it follows that $\frac{de^*}{dp} > 0$ and $\frac{d^2e^*}{d^2p} < 0$. Thus, we have the following two conjectures:

Conjecture 1: It is possible to increase a student's effort by increasing her belief in her ability to learn.

[1] "Grit" is another psychological construct designed to understands students' resilience. Grit emphasizes students' willingness to work no matter the circumstances. Growth mindset implies some level of grit. The key added element is students' prioritization of work which may be challenging but rewarding. For example, grit might encourage student to try on an easy and intellectually unrewarding task. A growth mindset would make no such prediction on such an easy, unrewarding task. A growth mindset operates in environments whether the task is challenging and rewarding.

Conjecture 2: The effort-effect of increasing the student's belief in her abilities to learn is higher, the lower the student's initial belief.

2.3 Academic Mindset Interventions

In psychology, a student's belief in her abilities to learn is referred to as her academic mindset (Dweck 2006). Students with a "fixed mindset" believe their intelligence or talents are fixed traits. Studies using survey measures of mindsets and experimental manipulations of mindsets in laboratory and school settings suggest that a fixed mindset shapes students' academic achievements in many ways (Dweck 2006, Yeager & Dweck 2012, Yeager & Walton 2011). First, fixed-mindset students avoid academic challenges. They want easier problems that will make them look and feel smart (Mueller & Dweck, 1998; Yeager et al., 2016). Second, a fixed mindset leads to unproductive beliefs about efforts. For example, a student with a fixed mindset might say, "If I have to try hard at math, I'm not smart at math" (Blackwell et al., 2007). Last, fixed-mindset students are less resilient. Instead, they hide setbacks and deficiencies, not wanting people to see them as having low ability. They fail to ask for help and sometimes even lie about low scores (Mueller & Dweck, 1998).

By contrast, students with "growth mindsets" believe that intelligence can grow and improve in response to efforts, good strategies, and help from others. From this perspective, an academic challenge is not a threat to one's ability; it is an opportunity for learning and improvement. In a growth mindset, effort is a good thing: a student might say "trying harder makes you smarter" (Blackwell et al., 2007). In the face of a difficult problem, a growth mindset student is more resilient, seeks appropriate help, or switches strategies. The student does not hide confusion. Unsurprisingly, holding a growth mindset predicts more learning, better learning strategies, and higher grades over time, as compared to a fixed mindset (Blackwell et al. 2007, Yeager & Dweck 2012).

There is substantial evidence suggesting that parents and teachers socialize children's mindsets through everyday communication (Kamins & Dweck 1999, Mueller & Dweck 1998, Rattan et al. 2015). Subtle verbal feedback from adults can put children in a fixed mindset and undermine internal motivation. This can happen even from valued caregivers trying to encourage children. For example, a classic paper by Mueller and Dweck (1998) showed that praising young adolescents for their intelligence – telling them they were "smart" when they did well – created a fixed mindset and undermined their resilience in the face of later struggle.

In contrast, praising students' "processes" (efforts or strategies) put children in a growth mindset and fostered resilience.

Recently several studies have demonstrated that precise theory-based interventions can communicate a growth mindset to youths and produce lasting improvements in students' grades (Aronson et al. 2002, Blackwell et al. 2007, Good et al. 2003, Paunesku et al. 2015, Yeager et al. 2016). These interventions appeal to neuroscience and evidence on the malleability of the brain. To communicate the malleability of intelligence, these interventions use physical exercise as a metaphor for growth mindset. The interventions teach the students to think of their brains as muscles, which get stronger as one exercises them. The intervention depicts new neuronal connections growing as students complete challenging math problems.

3. Experimental design

3.1. Intervention and Measures

We develop a computer program with three online sessions, each lasting about 45 minutes. We base content and visual layout in Sessions 1 and 2 on the intervention in Yeager et al. (2016) (also see Pauneksu et al., 2015). However, by the means of a professional translator and interviews with several focus groups of Norwegian high school students, we carefully adapted the material to the Norwegian language, culture and context. Session 3 consists of a real effort task in which the students have to solve a series of algebra questions. Figure 1 illustrates the content of the three sessions.

In Session 1 students first answer survey questions designed to measure students' mindsets at baseline.[2] In particular, we ask how much, on a scale from 1 to 6, the student disagrees (1) or agrees (6) with the following statements (assigned variable name in parenthesis):

- You have a certain amount of intelligence, and you really can't do much to change it" (Fixed Mindset 1);
- "Your intelligence is something about you that you can't change very much" (Fixed Mindset 2);
- "Being a "math person" or not is something that you really can't change. Some people are good at math and other people aren't" (Fixed Mindset Math); and

[2] Below, we only list survey questions used for this paper. The students received other survey items, designed to answer different research questions. All survey questions were identical for treated and non-treated.

- “When you have to try really hard in a subject in school, it means you can’t be good at that subject” (Fixed Mindset Effort).

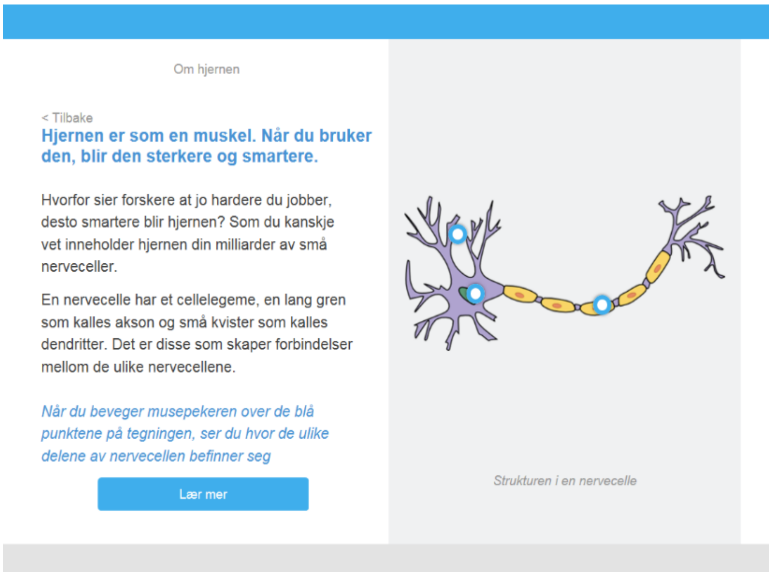
These mindset measures have been used and validated in numerous studies, demonstrating that they strongly predict grades and performance on behavioral tasks (see e.g. Burnette et al. 2013, Yeager et al. 2016)

Figure 1: Content of Computer Program

	Pre intervention measures	Intervention	Post intervention measures
Session 1	- Baseline Mindset measures	-Treated: Mindset -Control: Placebo	
Session 2		-Treated: Mindset -Control: Placebo	- Mindset Measures - Make a Math Worksheet
Session 3			- Solve Math Worksheet - Real Effort Task

After responding to the survey questions, the students receive the intervention. The computer program randomly allocates students to either the treatment or control conditions. The treated students have to do three cognitive exercises. First, students have to read an article about research in neuroscience that demonstrates the brain’s potential to grow and change, originally written for the experiment in Blackwell et al. (2007) and substantially revised in Yeager et al. (2016). The article presentation runs over several screens (one of which appears in a single screenshot in Figure 2) and has a stylized visual layout with illustrations. Second, students are asked to summarize the article and explain how its message relates to their own lives. Linking information to the self in this way makes it more self-relevant and easier to recall (Bower & Gilligan 1979, Hulleman & Harackiewicz 2009). Third, students are asked what growth mindset advice they might give to a friend who was struggling in school. This is because rehearsing how to respond to specific situations makes individuals more likely to enact the rehearsed behaviors in those situations (Gollwitzer 1999). The tactic of writing a letter to someone else is also employed to encourage students to internalize the ideas by endorsing them to someone else (see e.g. Aronson et al. 2002).

Figure 2: Screen shot from computer program.



Students in the control condition, like those in the treatment condition, read a brief article about the brain and answer reflective questions. However, they do not learn about the brain's malleability. Instead, they learn about basic brain functions and their localization, for example, the key functions associated with each cortical lobe. The experimental conditions are designed to look very similar to discourage students from comparing their materials. It involves the same type of graphic art – e.g. images of the brain, animations – as well as compelling stories.

After Session 1, treated students may understand the malleability of the brain, but they may not have reflected on why they might like to "grow their brains." As a result, Session 2 emphasizes a purpose for learning (Yeager et al., 2014) as a means for helping students internalize and adopt the growth mindset message and to apply it in their everyday learning activities. It does this by including prosocial, beyond-the-self motives for adopting and using a growth mindset (Grant 2013, Yeager et al. 2016). For example, one screen in the intervention reads as follows: "People tell us that they are excited to learn about a growth mindset because it helps them achieve the goals that matter to them and to people they care about. They use the mindset to learn in school so they can give back to the community and make a difference in the world later." Treated students also listen to older students talk about how a growth mindset helped them help others, and they learn about famous role models of a growth mindset. For instance, the treatment conveys the true story of Scott Forstall, who developed the first iPhone at Apple. Forstall used growth mindset research to select team members who were not afraid of failure but were ready for a challenge.

Similar to Session 1, the control students' activity in Session 2 is designed to be parallel to the treatment activity. Students learn more about the brain, but not about its malleability. They learn nothing of growth mindset. In general, we took every precaution to make sure that there was minimal to no contamination across treatment categories during implementation. Even if some contamination occurred after implementation (for example if students talked to each other about treatment material), the contamination would likely bias our estimated impacts downward given that the intervention likely did no harm but could serve to improve control students' outcomes.

After the intervention material, Session 2 provides the students with the same series of survey questions, measuring students' mindsets, as at the start of Session 1. Thereafter we include a measure of challenge seeking which prior research has associated with growth mindsets (Blackwell et al. 2007, Mueller & Dweck 1998). Similar to Yeager et al. (2016) we let students create their own math worksheet which they will have to work on in Session 3. Students can pick from easy questions from which they likely will not learn new skills, or hard questions, which may require more effort but provide more learning opportunities. As measures of students' challenge seeking, we use number of very hard questions selected and number of very hard or somewhat hard questions selected. The questions were provided by The Norwegian Directorate for Education and Training, and we categorized them into easy, hard and very hard based on previous students' scores on each question.

Finally, in Session 3 students first have to solve two randomly drawn questions from the worksheet they created in Session 2.[3] After the worksheet questions, the students have to participate in a real effort task, consisting of 34 multiple choice algebra questions, given sequentially.[4] The algebra questions were challenging, and several students did not have time to work on all the questions. On average, the students answered correctly 57, 44, and 24 percent of the first 10, 20 and 34 questions, respectively.

The on-screen introduction to the algebra questions tells the students that they will be given a series of algebra questions, and that they should try to do their best to find the correct answer. Moreover, it explains that students might learn something from working on the math

[3] We did not use this data, as selection in Session 2 (treatment affects challenge seeking) may affect performance on these questions. However, giving the students time in Session 3, to work on some questions from the worksheet, is still an important part of the design to avoid deception in Session 2.

[4] The first 13 questions were the same for all students. Thereafter, the computer program randomly assigned the students to one of three groups, and each group received the remaining algebra questions in different order.

questions, but that their performance will not affect their grade. As many students gave up or ran out of time on the last questions, we use number of correct questions on the first 10, 20, and all 34 questions as measures of students' effort on the algebra questions.

Notably, the students did not know that they would receive algebra questions in Session 3, so there was no way to prepare. Moreover, algebra was not on the curriculum in school between Session 1 and Session 3. Thus, if we find a treatment effect on these effort measures, it is reasonable to interpret it as an effect of effort (students are more focused on task, work harder and do not give up) and *not* that treated students have actually become better in algebra (although we can't rule out that some students may have been sufficiently motivated to pursue outside learning experience).

As a secondary matter, our data also allow us to investigate time spent on each algebra question. On the one hand, we could imagine that students with more perseverance manage to stay more focused and work harder and hence are able to move faster through the problems. On the other hand, given the difficulty of the questions, students with more perseverance may have spent more time trying to solve a question before giving up. They may have elected to try different approaches instead of making a random guess and moving on to the next question. As such, we do not have a clear hypothesis, as to how our intervention affected time use. When investigating time spent on the first 10, 20 or 32 minutes (results available from authors on request), we find no significant treatment effects neither on the full sample nor on relevant subsamples.

3.2. Hypotheses

Recall from the stylized model in Section 2.2, if the treatment increases a student's belief in her abilities to learn, this increases her marginal benefit of effort, and leads to an increase in the optimal effort level (Conjecture 1). As such, we hypothesize:

Hypothesis 1: The treatment has a positive effect on a student's effort in the real effort task in Session 3.

The stylized model also demonstrated that an increase in a student's belief in her abilities to learn, increases optimal effort level at a diminishing rate (Conjecture 2). As such, we hypothesize:

Hypothesis 2: Treatment effects on effort in the real effort task are larger for students who initially have low beliefs in their abilities to learn.

Hypotheses 2 is also consistent with several studies demonstrating that initially low performing students benefit more from mindset interventions, and that a fixed mindset is more common among these students pre-intervention (Paunesku et al. 2015, Yeager et al. 2016).

4. Sample and Procedures

In the spring of 2016, all first year students at a public high school in rural Norway participated in the field experiment. As the school serves a large region, it is large and offers both a vocational and academic track. Participation was mandatory as part of the school instruction, but students had to consent to participate in the research project. When the student logged on to the first session, they received information about the research project and had to make their consent decision. We had 458 students participate in the first session, among whom 385 students consented to participate in the research project.

After a student had made the consent decision, we randomly assigned the student to either the mindset or control condition. Among the students who consented, 22 students had missing registry data on middle school grades. Another 9 students were older than 20 years old.[5] Dropping these students from our sample resulted in a Session 1 sample of 354 students. Absence is a major concern in Norwegian high schools, and we experienced some attrition in Sessions 2 and 3. From our Session 1 sample, 289 and 254 students participated in Sessions 2 and 3, respectively. Our balance test (see Table 1) demonstrates that attrition was not significantly correlated with treatment status. Notably, we collected data for students in Session 3 even if they had not participated in Session 2, i.e. received the treatment reinforcement.

We implemented all sessions in the students' classroom during school hours. The students used their own laptop computers and headset.[6] At the beginning of each session, we read a brief script to all the students. We told the students that they were about to log onto a computer program designed to learn about the brain and reflect on learning. We asked the students to work independently and not talk to other students. We also emphasized that students should do their best and that their answers would be kept anonymous and not affect their grades. We assured them that their teacher or school would never see their individual answers. Finally, we told the students that the session would last for 45 minutes and provided them with logon information. In the first and second sessions, members of our research team administered the protocol with the teacher present in the classroom. In the third session, the teachers were

[5] This implies lagging behind statutory school progression by at least four years.
[6] A laptop is mandatory for school work. All the students have school district subsidized laptops. We had some extra headsets to lend to students who did not have headset.

responsible for implementation. We provided a script to them. Members of our research team were still present at the school in case the teachers had any questions or technical challenges. In all three sessions, if students finished prior to the 45 minutes, they were asked to work on other schoolwork. There are four open-ended questions in treated session 1. The frequency of students putting effort into the open-ended questions suggest that most students paid attention to the treatment material. 85 percent answered substantively, which was defined as any attempt of a sincere, non-ridiculous answer

Students logged on with a unique student number and password assigned to each student by the school district administration. Teachers were unaware of students' treatment status. For the students who consented, the school district provided us with registry data utilizing the same unique student number. The school district de-identified the data before they provided the data to our team. From the registry data, we employ the following variables: GPA and math grade[7] from middle school, high school track (indicator for vocational), gender (indicator for female) and age (indicator for being older than statutory age in first grade in high school).

5. Results

5.1 Balance Test and Descriptive Statistics

Table 1 presents our balance tests. Column 1 provides, for the Session 1 sample, the mean and the standard deviation for the control group for the pre-intervention variables. We can see that about 44 percent of the students are female; 58 percent are on the vocational track; and 9.1 percent of students are 1 or 2 years older than statutory age in first grade of high school All other covariates are standardized.

Using the sample for Session 1, we regress each covariate against treatment status. Column 2 presents the resulting coefficient and robust standard error on the treatment indicator. We can see that there are no significant differences between treated and control. Columns 3 and 4 and Columns 5 and 6 show, respectively, the results for students who participated in Session 2 and Session 3. Recall that all students in these latter sessions had participated in Session 1. Apart from the treatment indicator on female for the Session 2 sample, we find no significant differences between treatment and control. We conclude that randomization was successful and that attrition in Sessions 2 and 3 did not lead to significant differences in treatment status.

[7] Six students were registered without a math grade. These missing observations were replaced by predicted values (prediction based on baseline mindset measures, GPA, gender and vocational track). The correlation between predicted and observed values are .72. Results are robust with and without these students.

In Table 2 we present a correlation matrix of our mindset measures presented in Section 3.1. *Fixed Mindset 1*[8] and *Fixed Mindset 2* represent two different wordings of the same question, and it should not be surprising that they are highly correlated. We can also see that these direct measures of a fixed mindset are strongly correlated with our measures of having a fixed mindset when it comes to Math (*Fixed Mindset Math*) and Effort (*Fixed Mindset Effort*). These are more indirect measures which measure the consequences of having less of a growth mindset. Throughout we will use *Baseline Growth* as our mindset measure, which is the mean of our four fixed mindset metrics. In order to facilitate easier interpretations of the estimated coefficients, we reverse the mindset measure, so positive coefficients indicate more of a growth mindset.

In Table 3 we investigate how our pre-treatment covariates predicts a growth mindset. We can see in Columns 1-3 that the presence of growth mindset seems to be significantly more likely for students with high GPAs/math grade and for students who do not attend vocational tracks. Vocational tracks in Norway generally include students with lower academic credentials. In Column 5 we add all predictors to the same model and we find that there is only a significant relationship between GPA/math grade and growth mindset.

5.2 Treatment Effects

In Table 4 we investigate treatment effects on outcome measures gathered at the end of Session 2. First, we see if the treatment affected the measure of growth mindset. We gathered the same measures of mindset post-treatment as we did at baseline. *Post-Treatment Growth Mindset* is then constructed identically to our *Baseline Growth Mindset* variable. We can see from Column 1 that there is a large and significant effect of treatment on growth mindset. Indeed, treatment increases the score by 56 percent of a standard deviation. In Column 2 we can see that this finding is robust to controlling for our pre-intervention variables, including baseline growth mindset.

In columns 3-6, we investigate how treatment affected challenge seeking when students had to create their own math worksheet in Session 2. In Column 3, we see that treated students chose significantly more "very hard" questions compared to students in the control group. We can see that the estimate is robust to controlling for our pre-intervention variables in Column 4. It suggests that treatment increases challenge seeking by 29 percent of a standard deviation. In

[8] One student did not respond to the first fixed mindset question. This missing observation was replaced by the predicted value (prediction based on baseline mindset measures, GPA, gender and vocational track). The correlation between predicted and observed values are .70. Results are robust with and without this student.

Columns 5 and 6, we use number of "somewhat hard" or "very hard" questions as the outcome measure, and we get a similar treatment effect on this measure.

In Table 5, we investigate how treatment affected effort in the algebra questions in Session 3. Since some students did not have time to finish all the questions, or "gave up" – clicking fast through the questions,[9] we look at how many correct questions students had on the first 10, 20 and all 34 questions. In Column 1, we see no significant difference in effort on the first ten questions. However, when controlling for baseline variables in Column 2, we can see that treated students have significantly more correct answers on the first ten questions compared to students in the control group. Consistent with Hypothesis 1, the estimate suggests that treated students scored 19 percent of a standard deviation higher than control students. There were no significant differences between treated and control when investigating treatment effect on the first 20 or all 34 questions in Columns 3-6.

In Table 6 we investigate treatment effects for different subsamples. First, we characterize the students to have either a fixed or a growth pre-intervention mindset by splitting the sample at the median of our mindset measure. Consistent with Hypotheses 2, Panels A and B demonstrate that the treatment effect detected in Column 2 of Table 5 is entirely driven by students who initially had a fixed mindset. For these students, the treatment effect is large and significant for all three outcome measures. The estimates suggest that treated students scored 35, 34 and 29 percent of a standard deviation higher than control students on the first 10, 20 and all 34 questions, respectively. For students who initially had a growth mindset, there is no significant treatment effect; the estimated coefficient is even negative in all but one column.

In the remaining panels of Table 6 we investigate if there are observables from registry data that can identify students particularly responsive to treatment. Recall that Table 3 demonstrated that, prior to treatment, a fixed mindset is particularly prevalent among students with low GPA/math grade and students in the vocational track. Thus, we investigate treatment effect splitting the sample based on track and GPA (at the median).

In Panel C, we can see that among students in the vocational track there is a large and significant treatment effect. Looking at the first 10, 20 and all 34 questions, the treatment effect is 27, 25 and 25 percent of a standard deviation, respectively. Students in the academic track

[9] Eighteen students (7 percent) did not finish all questions. Among the 236 students who finished all questions, the average time per question declined. The first 13 questions took just under 50 seconds per question; questions 14-20 took on average about 40 seconds per question; questions 21-27 took about 30 seconds per question, and students spent just over 20 seconds per question on the remaining questions.

scored higher than other students, and as we show in Panel D, there is no significant treatment effect for them.

In Panel E we investigate treatment effect for students with a low pre-treatment GPA. We see that there is a significant treatment effect on all three outcome measures. Panel F demonstrates that there is no significant treatment effect on the students with a high pre-treatment GPA.

6. Discussion and Conclusion

Our results provide strong evidence that students' beliefs in their ability to learn are predictive of their subsequent perseverance. Moreover, we find strong evidence that these beliefs are malleable. As in prior studies, we only find effects on students who previously had a fixed mindset or had low achievement prior to the intervention. We find strong impacts of our treatment on these students' subsequent performance in a real effort task consisting of solving difficult algebra questions. To our knowledge, our paper is the first to draw a link between real-effort academic performance and experimentally manipulated academic mindset.

There are several implications to our research. First and foremost, improving student performance through a low-cost informational treatment has policy implications for schools and teachers. If teachers and schools can improve students' growth mindsets, academic performance, especially among the poorest performing students, can be raised.

Second, implementation costs of the treatment is very low: Rather than improving students' opportunities to learn through costly structural changes, it leads them towards better utilization of the learning opportunities already within the educational system (Yeager & Walton, 2011).

We only track students over a five-week period, and it remains to be seen whether the impacts we observed represent a change in students' beliefs and behavior beyond high school or whether the observed impacts will attenuate over time. We hope that our partnership with the school district might shed light on these more long-run impacts in future studies.

While the impact of academic mindset is relatively new to economics, many of its core elements – the willingness to take risks for potentially beneficial reasons, the perceived cost/benefit of effort, and the willingness to sacrifice current leisure for future benefits – have a long history of being studied in economics. Our hope is that future research can provide a tighter link between these complimentary literatures.

References

Alan, S., Boneva, T., & Ertac, S. (2015). *Ever Failed, Try Again, Succeed Better: Results from a Randomized Educational Intervention on Grit*. Retrieved from

Aronson, J., Fried, C. B., & Good, C. (2002). Reducing the effects of stereotype threat on African American college students by shaping theories of intelligence. *Journal of Experimental Social Psychology, 38*(2), 113-125.

Azmat, G., & Iriberri, N. (2010). The importance of relative performance feedback information: Evidence from a natural experiment using high school students. *Journal of Public Economics, 94*(7), 435-452.

Bettinger, E. P., Long, B. T., Oreopoulos, P., & Sanbonmatsu, L. (2012). The role of application assistance and information in college decisions: Results from the h&r block fafsa experiment*. *The Quarterly Journal of Economics, 127*(3), 1205-1242.

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child development, 78*(1), 246-263.

Borghans, L., Duckworth, A. L., Heckman, J. J., & Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources, 43*(4), 972-1059.

Bower, G. H., & Gilligan, S. G. (1979). Remembering information related to one's self. *Journal of Research in Personality, 13*(4), 420-432.

Bradler, C., Dur, R., Neckermann, S., & Non, A. (2016). Employee recognition and performance: A field experiment. *Management Science*.

Burnette, J. L., O'Boyle, E. H., VanEpps, E. M., Pollack, J. M., & Finkel, E. J. (2013). Mind-sets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin, 139*(3), 655.

Carrell, S. E., Kurlaender, M., & Bhatt, M. P. (2016). Experimental Evidence of Professor Engagement on Student Outcomes. *Working Paper*.

Castleman, B. L., & Page, L. C. (2015). Summer nudging: Can personalized text messages and peer mentor outreach increase college going among low-income high school graduates? *Journal of Economic Behavior & Organization, 115*, 144-160.

Cohen, G. L., & Sherman, D. K. (2014). The psychology of change: Self-affirmation and social psychological intervention. *Annual Review of Psychology, 65*, 333-371.

Dweck, C. (2006). *Mindset: The new psychology of success*: Random House.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological review, 95*(2), 256.

Eriksson, T., Poulsen, A., & Villeval, M. C. (2009). Feedback and incentives: Experimental evidence. *Labour Economics, 16*(6), 679-688.

Gollwitzer, P. M. (1999). Implementation intentions: strong effects of simple plans. *American psychologist, 54*(7), 493.

Good, C., Aronson, J., & Inzlicht, M. (2003). Improving adolescents' standardized test performance: An intervention to reduce the effects of stereotype threat. *Journal of Applied Developmental Psychology, 24*(6), 645-662.

Grant, A. (2013). *Give and take: Why helping others drives our success*: Penguin.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics, 24*(3), 411-482.

Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science, 326*(5958), 1410-1412.

Kamins, M. L., & Dweck, C. S. (1999). Person versus process praise and criticism: implications for contingent self-worth and coping. *Developmental psychology, 35*(3), 835.
Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., & Borghans, L. (2014). *Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success*. Retrieved from
Koch, A., Nafziger, J., & Nielsen, H. S. (2015). Behavioral economics of education. *Journal of Economic Behavior & Organization, 115*, 3-17.
Kvaløy, O., Nieken, P., & Schöttner, A. (2015). Hidden benefits of reward: A field experiment on motivation and monetary incentives. *European Economic Review, 76*, 188-199.
Lavecchia, A. M., Liu, H., & Oreopoulos, P. (2014). *Behavioral economics of education: Progress and possibilities*. Retrieved from
Mueller, C. M., & Dweck, C. S. (1998). Praise for intelligence can undermine children's motivation and performance. *Journal of personality and social psychology, 75*(1), 33.
Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological science*, 0956797615571017.
Rattan, A., Savani, K., Chugh, D., & Dweck, C. S. (2015). Leveraging Mindsets to Promote Academic Achievement Policy Recommendations. *Perspectives on Psychological Science, 10*(6), 721-726.
Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science, 2*(4), 313-345.
Walton, G. M. (2014). The new science of wise psychological interventions. *Current Directions in Psychological Science, 23*(1), 73-82.
Wilson, T. D., & Buttrick, N. R. (2016). New directions in social psychological interventions to improve academic achievement. *Journal of Educational Psychology, 108*(3), 392.
Yeager, D. S., & Dweck, C. S. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist, 47*(4), 302-314.
Yeager, D. S., Romero, C., Paunesku, D., Hulleman, C. S., Schneider, B., Hinojosa, C., . . . Roberts, A. (2016). Using design thinking to improve psychological interventions: The case of the growth mindset during the transition to high school. *Journal of Educational Psychology, 108*(3), 374.
Yeager, D. S., & Walton, G. M. (2011). Social-psychological interventions in education They're not magic. *Review of Educational Research, 81*(2), 267-301.

Tables

Table 1: Balance Test

	Session 1		Session 2		Session 3	
	Control	Treatment	Control	Treatment	Control	Treatment
GPA	.083	-.165	.165	-.072	.224	-.083
	(.916)	(.106)	(.809)	(.101)	(.892)	(.121)
Math grade	.066	-.130	.130	-.067	.172	-.031
	(.970)	(.106)	(.940)	(.115)	(.956)	(.125)
Vocational	.583	.082	.566	.080	.489	.073
		(.051)		(.057)		(.063)
Female	.440	.085	.441	$.107^{+}$	.511	.084
		(.053)		(.059)		(.062)
Old_age	.091	-.013	.055	-.027	.075	-.017
		(.030)	(.304)	(-.023)	(.265)	(.031)
Fixed Mindset 1	.049	-.096	.008	-.071	.036	-.144
	(.996)	(.106)	(.977)	(.115)	(.988)	(.124)
Fixed Mindset 2	.041	-.081	.046	-.097	.027	-.074
	(.993)	(.106)	(.988)	(.116)	(.957)	(.121)
Fixed Mindset Math	.047	-.092	.040	-.150	.029	-.063
	(1.013)	(.106)	(.974)	(.114)	(.968)	(.120)
Fixed Mindset Effort	-.035	.070	-.111	.112	-.090	.135
	(.965)	(.106)	(.885)	(.110)	(.906)	(.121)
Baseline growth	-.038	.075	.001	.078	-.005	.059
	(.1.020)	(.106)	(.968)	(.112)	(.984)	(.122)
N	175	354	145	289	133	254

Notes: $^{+}$ p<0.10, * p<0.05, ** p<0.01. For each session sample, columns labeled control provide the mean (standard deviation) for the control group, and columns labeled treatment provide the estimated coefficient (robust standard error) from regressing each covariate against treatment status.

Table 2: Correlation between Pre-Treatment Mindset Measures

	Fixed Mindset 1	Fixed Mindset 2	Fixed Math Mindset	Fixed Effort Mindset
Fixed Mindset 2	.690**			
Mixed Math Mindset	.281**	.425**		
Fixed Effort Mindset	.212**	.322**	.299**	
Baseline Growth Mindset	-.765**	-.845**	-.696**	-.600**

Notes: $^{+}$ p<0.10, * p<0.05, ** p<0.01. Session 1 sample (n=354).

Table 3: Predictors of Baseline Growth Mindset

	(1)	(2)	(3)	(4)	(5)	(6)
GPA	.250**					.139^{+}
	(.052)					(.077)
Math grade		.260**				.179*
		(.051)				(.075)
Vocational			-.282*			.053
			(.109)			(.129)
Female				.151		.082
				(.106)		(.105)
Old_ a~~A~~ge					-.157	.107
					(.191)	(.193)
R-squared	.060	.065	.016	.003	.003	.066

Notes: $^{+}$ p<0.10, * p<0.05, ** p<0.01. Dependent variable: Baseline Growth Mindset. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for all included covariates. Session 1 sample (n=354).

Table 4: Treatment Effect on Post-Treatment Mindset and Challenge Seeking in Session 2

	Post-Treatment Growth Mindset		Choosing "Very Hard" Challenge Questions		Choosing "Hard" or "Very Hard" Challenge Questions	
	(1)	(2)	(7)	(8)	(9)	(10)
Treatment	.557**	.545**	.234*	.285**	.240**	.300**
	(.113)	(.090)	(.117)	(.110)	(.117)	(.111)
GPA		.055		.040		.119
		(.085)		(.105)		(.105)
Math grade		.228**		.378**		.407**
		(.068)		(.084)		(.084)
Vocational		.006		.159		-.006
		(.114)		(.140)		(.140)
Female		.002		-.468**		-.417**
		(.092)		(.113)		(.114)
Old_age		.323		-.204		-.094
		(.225)		(.277)		(.277)
Baseline Growth		.522**		.045		.020
		(.048)		(.059)		(.059)
R-squared	.075	.435	.010	.144	.011	.141

Notes: + p<0.10, * p<0.05, ** p<0.01. First row lists the dependent variable. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for all included covariates. Session 2 sample (n=289). For columns (1) and (2): n=288.

Table 5: Treatment Effect on Effort in Session 3

	Score on First 10 Questions		Score on First 20 Questions		Score on All 34 Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.121	.193*	.057	.134	.012	.089
	(.126)	(.089)	(.126)	(.085)	(.126)	(.086)
GPA		-.036		.004		-.028
		(.072)		(.068)		(.069)
Math grade		.542**		.582**		.551**
		(.067)		(.063)		(.064)
Vocational		-.643**		-.542**		-.602**
		(.110)		(.103)		(.106)
Female		-.081		-.134		-.176*
		(.092)		(.086)		(.088)
Old_age		.492**		.464**		.304+
		(.184)		(.172)		(.176)
Baseline growth		.021		.068		.102*
		(.048)		(.045)		(.046)
R-squared	.000	.506	.003	.567	.004	.544

Notes: + p<0.10, * p<0.05, ** p<0.01. First row lists the dependent variable. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for included covariates. All included covariates are reported, except from in columns 2, 4 and 6 where we additionally control for question assignment order (two indicators). Session 3 sample (n=254).

Table 6: Treatment Effect on Effort in Session 3. Subsample analyses

	Score on First 10 Questions		Score on First 20 Questions		Score on All 34 Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pre-Treatment Fixed Mindset (n=130)						
Treatment	.297^{+}	.348*	.299^{+}	.335**	.245	.285*
	(.178)	(.135)	(.170)	(.117)	(.170)	(.116)
Adj R-squared	.014	.434	.016	.538	.008	.540
Panel B: Pre-Treatment Growth Mindset (n=124)						
Treatment	-.094	.022	-.227	-.059	-.266	-.129
	(.165)	(.114)	(.172)	(.119)	(.169)	(.121)
Adj R-squared	.005	.553	.006	.563	.012	0.530
Panel C: Vocational Track (n=133)						
Treatment	.234^{+}	.272*	.217^{+}	.253*	.222^{+}	.251*
	(.133)	(.128)	(.117)	(.109)	(.119)	(.114)
Adj R-squared	.016	.131	.018	.189	.018	.143
Panel D: Academic Track (n=121)						
Treatment	.172	.088	.056	-.029	-.043	-.110
	(.162)	(.122)	(.178)	(.116)	(.173)	(.121)
Adj R-squared	.001	.449	.008	.584	.008	.524
Panel E: Low GPA (n=129)						
Treatment	.180	.286*	.156	.226*	.121	.191^{+}
	(.135)	(.128)	(.115)	(.108)	(.114)	(.106)
Adj R-squared	.006	.146	.007	.165	.001	.171
Panel F: High GPA (n=125)						
Treatment	.148	.074	.053	-.030	-.006	-.078
	(.165)	(.125)	(.169)	(.123)	(.174)	(.131)
Adj R-squared	.002	.458	.007	.496	.008	.459
Control variables included		yes		yes		Yes

Notes: $^{+}$ p<0.10, * p<0.05, ** p<0.01. First row lists the dependent variable. Each panel represents a different sample. For given sample, each row presents a separate regression and reports the estimated treatment coefficient (robust standard error) and adjusted R-square. Last rows indicate whether the regression includes the control variables. The control variables are GPA, math grade, vocational track (indicator), female (indicator), age, and question assignment order (two indicators).