Skills Accumulation with Malleable Ability: Evidence from a Growth Mindset Intervention

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Abstract

Existing research shows that students endowed with "growth mindset"; a belief that one's intelligence and cognitive abilities are malleable so can be increased through effort, rather than fixed traits; are more likely to be academically successful. Interventions attempting to inculcate beliefs, particularly in groups with low academic performance, have therefore been posited as a way to improve, or close ethnic or social gaps in, students' performance. However, the mechanisms through which the claimed benefits are found are poorly understood. In this paper we evaluate the effects of a randomized light touch intervention given to first year university students in the UK on a validated growth mindset scale, their subjective beliefs about the production function for educational performance, and various measures of study habits measured two months later, compared with baseline pre-treatment measures and a control intervention. We document a positive treatment effect on student grades, and show this to be consistent with students acting on a change in their subjective production technology to make an hour of study effort more efficient through increasing the proportion spent in active learning methods, and spacing out study of the same material.

JEL classifications: C91; D84; D91; I21; I23

Keywords: Growth mindset; Beliefs; Randomized Control Trial; Higher Education; Educational investments

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1 Introduction

There is growing evidence that non-cognitive skills, meaning personality traits, attitudes or social-emotional skills, play a crucial role in explaining educational and social outcomes (Almlund et al., 2011; Borghans et al., 2008; Heckman and Kautz, 2012, 2013, 2014; Kautz and Zanoni, 2014). Moreover, several of these skills have been shown to be malleable, raising the possibility that interventions can be designed to manipulate and harness them to increase educational attainment or individual well-being.

Growth mindset; a belief that one's intelligence and cognitive abilities are malleable so can be increased through effort, rather than fixed traits; is one such malleable non-cognitive trait. (Dweck, 2006). Interventions attempting to inculcate this belief, particularly in groups with low academic performance, have been posited as a way to improve, or close ethnic or social gaps in, students' performance (Aronson et al., 2002; Good and Aronson, 2008). There is an extensive literature on the association between mindset and people's conception of their learning and personal characteristics (Dweck, 2006; Dweck et al., 1995; Dweck and Legget, 1998; Molden and Dweck; 2006), or the meaning of failures (Dweck, 2006) but the mechanisms through which the claimed benefits of growth mindset for educational outcomes are found are poorly understood.

In this paper we make an advance by bring together evidence on students' growth mindset, subjective beliefs about the production function for educational performance, and a wide range of measures of study habits. We do this by exploiting the effects of a randomized light touch intervention given to first year university students in the UK on a validated growth mindset scale and students' probabilistic beliefs about educational outcomes conditional on study and attendance inputs. We use a rich set of data collected as part of a longitudinal study of one cohort of undergraduate students, on students' pre-treatment behaviour and post-treament behavioural responses from time diaries, administrative records of attendance at lectures and classes, the composition of self-reported hours of study into categories such as testing, note-taking and reading, and study habits such as cramming and working with others, all compared with a control group. The majority of our follow-up measures are taken two months later, meaning our findings represent persistent effects compared with within-lab studies of changes in beliefs.

The intervention took place in the middle of their first year of study, and comprised a 10 minute video which (i) explained how people's brain can grow and adapt in response to learning opportunities and (ii) provided some specific study tips that would prompt the brain to be challenged (e.g., testing oneself instead of reading, or spacing out study practice over time), followed by two incentivised tasks designed to test their comprehension of the information, and how its lessons could be implemented.

The first-stage treatment effect of the intervention was to increase growth mindset by approximately 25% of a standard deviation; academic performance (Grade Point Average) by 17% of a standard deviation and the probability of this mark surpassing the threshold for the highest 'degree class' in the UK system by 5.7 percentage points. We show this to be consistent with students acting on a change in their subjective production technology for educational performance - the treatment effect in student's expected probability of getting a 'good degree class', holding constant their overall time allocation of study and attendane, is 1.3 percentage points. We show a significant change in the composition of study time and habits for treated students, decreasing weekly study hours by 4.64 hours in the summer revision period, and increasing the proportion of this study in active learning methods by 9.6 percentage points over the same period. They also had a greater propensity to space out study of the same material, altogether making an hour of study effort more efficient.

The rest of the paper is organized as follows: Section 2 presents the theoretical framework, Section 3 presents data, Section 4 describes the intervention, Section 5 explains empirical strategy, Section 6 shows and discusses results and Section 7 concludes.

2 Theoretical Framework

In this section, we develop a simple model of human capital formation. A student lives for $T+1$ periods. In period $t=0$, the first period of his life, student i acquires higher education. At the end of the period, he leaves university and enters the labor market where he stays till period $t=1...T$: His utility depends on consumption, on amenities enjoyed at university (such as social life and pleasure from learning) and on effort exerted while at university. For tractability, we assume that the utility function is additively separable, linear in university amenity, and logarithmic in consumption. Thus, the utility of individual i s is given by:

$$U_I(e, c_{it}) = \alpha S - c(e) + \theta \sum_{t=0}^{T} \beta^t ln(C_{it}) + \epsilon_i$$

where α is the utility value of amenity $S, c(e)$ is a strictly increasing convex cost function for exerting effort e ($e\epsilon[0; E], c'(e) > 0$ and $c"(e) \geq 0$), β is the time preference discount factor, C_{it} is is consumption at time t, θ is the utility value of log consumption, and ϵ_i is a random term which is individual-specfic and unobservable to the econometrician. The effort e includes the time spent on academic investments, as well as how this time is spent.

There is no borrowing or lending possible so student i will consume his earnings y_{it} at every period from t= 1 to T. At time $t=0$, i needs to finance his schooling out of his parents earnings y_{i0} and he faces tuition fee F. His per-period budget constraints are therefore given by:

$$C_{i0} + F \leq y_{i0}$$
$$C_{it} = y_{it} \text{ for } t = 1 \text{ to } T$$

In this set-up, the student's most important decision is how much effort to exert in school. The choice is important because it affects the stream of (expected) future earnings (and thus consumption) but also the cost of effort while at university. Student i holds subjective beliefs about how his final grade influences his future earnings $y_{it}(g)$, (with $\frac{\partial y_{it}(g)}{\partial g} \geq 0$) the probability of being employed $P_{it}(g)$, (with $\frac{\partial P_{it}(g)}{\partial g} \geq 0$). He also has subjective beliefs about how his final grade g is determined by his perceived ability and effort e.

$$g = g_i(a_i(e), e),$$

where $a_i(e)$ denotes i's perceived ability. We have $\frac{\partial g_i}{\partial a_i} \geq 0$ and $\frac{\partial g_i}{\partial e} \geq 0$.

For individual with a **fixed mindset**,$a_i(e) = a_i$ for all $e\epsilon[0; E]$. For people with a **growth mindset**, $\frac{\partial a_i}{\partial e} \geq 0$ for all $e\epsilon[0; E]$, and $\frac{\partial a_i}{\partial e} \geq 0$ for some $e\epsilon[0; E]$.
This means that the overall return to effort in terms of grade will be higher in the growth mindset than in the fixed mindset $((\frac{\partial g(a_i,e)}{\partial a_i}\frac{\partial a_i(e)}{\partial e} + \frac{\partial g(a_i,e)}{\partial e}) \geq (\frac{\partial g_i(a_i,e)}{\partial e}))$

Because we assume no borrowing or lending, the student will consume his earning every period. He therefore only needs to choose the effort e that maximizes his lifetime expected utility

$$max_e \quad \alpha S - c(e) + \theta ln(y_{i0} - F) + \theta \sum_{t=1}^{T} \beta^t \left\{ P_{it}(g_i(a_i, e)) ln(y_{it}(g_i(a_i, e)) + (1 - P_{it}(g_i(a_i, e))) ln(b) \right\} + e_i$$

(2)

Here b are unemployment benefits. Unemployment benefits are assumed to be lower than wages, i.e., $y_{it} \geq b$ for all t and i. Lets further assume that the subjective probability of employment is time-invariant, i.e. $P_{it}(g_i(a_i,e)) = P_i(g_i(a_i,e))$ and that the students have belief that earnings will grow at an annual rate of $r_i$such that

$$y_{it+1} = y_{it}^{r_i}$$

i.e

$$y_{it+1} = y_{i0}^{tr_i}$$

With these assumptions, we can re-write the maximization problem (2) as:

$$max_e \quad \alpha S - c(e) + \theta ln(y_{i0} - F) + \theta \sum_{t=0}^{T} \beta^t \left\{ P_i(g_i(a_i,e)) tr_i ln(y_{i1}(g_i(a_i,e)) + (1 - P_i(g_i(a_i,e))) ln(b) \right\} + e_i$$

(3)

which is equivalent to

$$max_e \quad \alpha S - c(e) + \theta ln(y_{i0} - F) + \theta^* P_i(g_i(a_i,e)) ln(y_{i1}(g_i(a_i,e)) + \theta^{**}(1 - P_i(g_i(a_i,e))) + e_i$$

(4)

where $\theta^* = \theta \sum_{t=1}^{T} \beta^t tr_i$and $\theta^{**} = \theta \sum_{t=1}^{T} \beta^t ln(b)$

The F.O.C with respect to e is then given by:

$c'(e) = (\frac{\partial g_i(a_i,e)}{\partial a_i} \frac{\partial a_i(e)}{\partial e} + \frac{\partial g_i(a_i,e)}{\partial e})$ x $\left[\frac{\partial P_i(g_i(a_i,e))}{\partial g_i} (\theta^* ln(y_{i1}(g_i(a_i,e)) - \theta^{**}) + (\theta^* \frac{P_i(g_i(a_i,e))}{y_{i1}(g_i(a_i,e)} \frac{\partial y_{i1}(g_i(a_i,e)}{\partial g_i} \right]$

We have: $\frac{\partial P_i(g_i(a_i,e))}{\partial g_i} \geq 0$ and $\frac{\partial y_{i1}(g_i(a_i,e)}{\partial g_i} \geq 0$. Moreover $\theta^* ln(y_{i1}(g_i(a_i,e)) - \theta^{**} = \theta \sum_{t=1}^{T} \beta^t ln(y_{it)} - ln(b) \geq 0$.

Let $\Gamma_i(c) = \left[\frac{\partial P_i(g_i(a_i,e))}{\partial g_i} (\theta^* ln(y_{i1}(g_i(a_i,e)) - \theta^{**}) + \theta^* \frac{P_i(g_i(a_i,e))}{y_{i1}(g_i(a_i,e)} \frac{\partial y_{i1}(g_i(a_i,e)}{\partial g_i} \right]$

The model delivers the following implications:

Implication 1: Consider two students i and j with identical beliefs except that i has a growth mindset and j has a fixed mindset. Student i will exert more effort than student j. Under the fixed mindset, the optimal amount of effort e^f is given by $c'(e) = \frac{\partial g_i(a_i,e)}{\partial e} \Gamma_i(e)$.Under the growth mindset, the optimal amount of effort $e^g$is given by $c'(e) = (\frac{\partial g_i(a_i,e)}{\partial a_i}\frac{\partial a_i(e)}{\partial e} + \frac{\partial g_i(a_i,e)}{\partial e})\Gamma_i(e)$.Note that $\frac{\partial g(a_i,e)}{\partial a_i}\frac{\partial a_i(e)}{\partial e} \geq 0$ for all e, so $(\frac{\partial g_i(a_i,e)}{\partial a_i}\frac{\partial a_i(e)}{\partial e} + \frac{\partial g_i(a_i,e)}{\partial e})\Gamma_i(e) > \frac{\partial g_i(a_i,e)}{\partial e}\Gamma_i(e)$ for all e.

Because $c'(e) > 0$, we have $e^g > e^f$.

Note that this is under the assumption that we do not reach a corner solution. That would be the case if E is large enough.

Implication 2: Consider two students i and j with the same beliefs $\partial g_i(a_i, e)$. If student i has a growth mindset and j has a fixed mindset, student i believes that the return to effort in terms of grade are larger than student j.

3 Data

3.1 BOOST2018 Study

BOOST2018 is a longitudinal survey of undergraduate students at a research-intensive UK university. The survey followed a cohort of undergraduate students who started in October 2015 from their first term through to the completion of their higher education degree in Spring 2018. It records students' behaviours, beliefs, expectations and aspirations about the future and how these change over time. As well as being large in size, with approximately 2000 participants, the intake is unusually mixed in terms of socioeconomic and educational backgrounds, and broadly representative of the UK Higher Education population as a whole.

Enrolment took place in October 2015. Students were approached while queuing up to register for their courses, at 'Freshers' Fair' where students could also join Student Union clubs and societies, and during breaks in the middle of lectures in the first week of term. They could also enroll online. On enrolment they were given £5 in cash to say thank-you, and promised that they would receive at least £10 for each full online survey they completed, with seven waves initially advertised.

We defined our target population as non-returning first year undergraduate students on Bachelors courses. The majority of these (i.e. those completing a degree in three years) graduated in summer 2018. The sample frame consisted of 2621 students, of whom 1981 gave their consent, which was required before contacting them to participate in any survey. This consent included permission to access administrative data already held by the university on their demographic characteristics and prior educational performance, their course enrolment and attendance records, and coursework and exam results.

Participants were interviewed 4 times a year for 3 years: they reply to a long online survey in November and March (60 min), a short online survey during the revision period (April), and are invited to come into an experimental laboratory in January. Approximately 1,200 respondents replied to each online survey and 1,000 came into the lab each year. In this paper, we focus on the first year of data. The intervention studied in this paper was implemented in the first year lab session ("wave 2").

Survey responses are linked with administrative data on academic performance (individual-level marks on all 'for-credit' modules students took), individual attendance to lectures and classes ("Count-me-in data" obtained from students swiping their card at entrance to classroom), and demographic characteristics.

3.2 Students' Demographic Characteristics

We summarisze demographic characteristics of the students in Table 1. About 10% of the cohort and 8% of the respondents are "Mature" students, defined as aged 21 or older on entry to university. Using administrative data, we distinguish between 'Home', non-British EU, and non-EU 'Overseas' students, and further decompose the 'Home' students first by ethnicity, and for the White students, socioeconomic status (SES). Black, Asian and "White Working Class" (i.e. White British Low SES") classifications are important groupings for potential stereotyp threat. We categorize high versus low SES using the student's parental occupation, with "Managerial and professional" and "Intermediate" occupations classified as High SES, and the rest (including small employers, technical, semi-routine and routine occupaations, and long-term unemployed) as Low SES. In cases where parental occupation is missing, we classify those whose neighbourhood of domicile is in the top 40% nationally the for youth higher education participation rate as High SES, and the rest as Low SES.

While the number of male and female eligible students are similar to each other in the eligible subsample, fewer male students signed up to the study and even fewer male students participated at least one wave in the first year of the study. White High and Low SES students' portions are very similar in all three samples, while Black British students and Overseas students are more likely to participate and Asian British and EU students are less likely to participate.

	Essex		Signed Up		Year 1	
	N	%	N	%	N	%
Male	1304	49.75	949	47.98	688	44.73
Female	1317	50.25	1029	52.02	850	55.27
White High SES	643	24.50	481	24.32	368	23.93
White Low SES	402	15.31	301	15.22	233	15.15
Black British	365	13.90	299	15.12	232	15.08
Asian British	258	9.83	149	7.53	123	8.00
Other British	227	8.65	163	8.24	127	8.26
EU	425	16.19	312	15.77	262	12.55
Overseas	305	11.62	273	13.80	193	17.04
Mature	250	9.54	161	8.14	121	7.88
Young	2371	90.46	1817	91.86	1415	92.12

Table 1: Characteristics of the Students

3.3 Educational Achievement

We have administrative data for the grades for all the courses a student takes. In particular, we have final exam grade, coursework grade and overall final grade, all measured on a 0-100 scale. Because the intervention was fielded in the first year, our main focus is on year 1 grades. We calculate student's weighted average final grades for each year. Note that many courses are year-long courses with some coursework in the fall semester, i.e., before the intervention. Exams, however, are all taken at the end of the academic year. We therefore also look at exam grades as an outcome. As we do with the final grade, we calculate the weighted average exam grades of the students.

In addition to the continuous grades, we consider the prospective "degree class" these correspond to. 70 or higher is "First class", 60-69 is "Upper second class", 50-59 "Lower second class", 40-49 a "Third class" and below this a fail. This is a meaningful outcome, as although full course transcripts containing grades are produced in the UK, employers' requirements are usually expressed in terms of the applicant's final degree class (most commonly a 'good degree' of upper second class or better), and this is the most prominent indicator of performance on indivdiuals' curricula vitae.

3.4 Academic Inputs

3.4.1 Attendance

We use administrative data on each student's attendance to each lectures and classes, aggregating these data to produce summary measures of the the autumn and spring term attendance rate. The short summer term immediately preceding the exam period does not have lectures but only few revision classes.

Table 2 shows autumn term attendance along with other measures of inputs collected in the survey wave 1. Female students attend more lectures than male students and this difference is significant at the 1% level. Black British and Other British students are less likely to attend the lectures than white High SES British students. There is no significant difference between mature and young students.

3.4.2 Weekly Study Hours

We use self-reported weekly study hours. In the survey, students are asked "Not counting the hours spent in class and lectures, how many hours in a typical week during tem time do you usually study?". We have data for this variable in wave 1, 3 and 4.

Table 2 shows weekly study hours for wave 1. Female students spend more time on studying than males and Black British students spend more time studying than any other ethnic group. Mature students spend more time studying than young students. While the differences between male and female, and between young and mature students is significant at the 1% level, there is no significant difference by ethnicity.

3.4.3 Active Learning

After answering the question about weekly study hours, students are asked about the composition of these study hours. They were asked to allocate their reported total study hours to the 5 following categories: (i) Doing compulsory homework (essays, exercises, etc.), (ii) Reading or re-reading textbooks or course materials, (iii) Paraphrasing or making notes, copies, outlines, or annotations from textbooks or course materials, (iv) Testing yourself with questions, practice problems, past exams or flash cards and (v) other. Previous studies show that testing oneself and doing homework are very effective methods of learning (Dunlosky et al., 2013). We calculated percentage of study hours spent on "active learning" as the sum of the proportions spent on compulsory homework and testing (there are no assignments in the summer revision period so the wave 4 figure corresponds only to testing).

These proportions are shown in Table 2. Male students spend a higher proportion of their study time doing active learning than females and this is significant at 1% significance level. While Overseas students spend the highest proportion doing active learning, the differences in ethnicity are not significant. Mature students are found to do less active learning than their young peers but this difference is significant only at 10%.

3.5 Academic Habits

Further explicit measures of study habits are collected using Likert-scale type questions, to elicit more information about the character and context of the reported study time.

3.5.1 Cramming

Cramming is measured by a simple question "I 'cram' lots of information the night before I have a test". The answer to this question is a Likert-scale with 4 possible choices; Never, Sometimes, Often and Always. We define a dummy variable for cramming that takes the value of 1 if the respondent answers Often and Always, 0 otherwise. We have data on cramming on wave 1, 3 and 4.

Table 2 shows cramming for different groups. We do not find any difference between gender, ethnicity or age groups.

3.5.2 Studying with friends and studying in the same place

Similar to cramming, studying with friends is measured by a simple question "I study with friends" and studying in the same place is measure by "I study in the same place" The answer to these questions is a Likert-scale with 4 possible choices; Never, Sometimes, Often and Always. We define dummy variables for studying with friends and studying in the same place that takes the value of 1 if the respondent answers Often and Always, 0 otherwise. We have data on studying with friends and studying in the same place in wave 1, 3 and 4.

Table 2 shows studying with friends and studying in the same place. We do not find any difference between gender, ethnicity or age groups for studying with friends. We find that black British students study less in the same place than white British High SES students and this difference is significant. We also find that mature students study more in the same place than their young peers.

3.5.3 Spacing Out

Similar to previous habits, spacing out is measure by a simple question "I space out studying of a specific topic over different days and weeks." The answer to this question is a Likert-scale with 4 possible choices; Never, Sometimes, Often and Always. We define a dummy variable for studying with friends and studying in the same place that takes the value of 1 if the respondent answers Often and Always, 0 otherwise. We have data on spacing out only in wave 4 so our analyses using this variable will employ a slightly different technique.

	Attendance	Weekly Study Hours	Active Learning	Cramming	Studying with Friends	Studying in the Same Place	Growth Mindset Score
Female	0.70***	14***	0.53**	0.39	0.20	0.76	37.16***
	(0.18)	(10.89)	(0.2)	(0.49)	(0.40)	(0.43)	(8.9)
Male	0.68	11.26	0.55	0.42	0.22	0.78	35.17
	(0.19)	(10.24)	(0.22)	(0.49)	(0.42)	(0.41)	(9.14)
White H	0.71	11.80	0.55	0.44	0.18	0.83	36.56
	(0.18)	(9.13)	(0.22)	(0.5)	(0.38)	(0.38)	(9.20)
White L	0.70	11.57	0.54	0.45	0.16	0.78	36.04
	(0.17)	(9.84)	(0.22)	(0.5)	(0.37)	(0.41)	(9.51)
Black B	0.64***	14.59*	0.53	0.31	0.27	0.66***	37.95
	(0.18)	(13.20)	(0.22)	(0.47)	(0.44)	(0.47)	(9)
Asian B	0.66	13.16	0.52	0.39	0.22	0.70	36.49
	(0.18)	(12.18)	(0.22)	(0.49)	(0.41)	(0.46)	(7.88)
EU	0.74	13.84	0.52	0.36	0.20	0.81	35.78
	(0.16)	(10.49)	(0.19)	(0.48)	(0.40)	(0.39)	(9.08)
Overseas	0.73	13.56	0.56	0.43	0.22	0.74	34.82
	(0.16)	(11.52)	(0.19)	(0.5)	(0.42)	(0.44)	(8.79)
Other B	0.59***	11.18	0.53	0.42	0.29	0.75	36.31
	(0.25)	(9.46)	(0.20)	(0.5)	(0.46)	(0.44)	(9)
Mature	0.68	14.14**	0.53*	0.31	0.20	0.87**	36.79
	(0.23)	(11.72)	(0.20)	(0.46)	(0.40)	(0.34)	(11.01)
Young	0.69	12.61	0.54	0.41	0.21	0.76	36.24
	(0.18)	(10.59)	(0.21)	(0.49)	(0.41)	(0.43)	(8.86)

* significant at 10%, ** significant at 5%, *** significant at 1% (for ethnicity, base category is White High SES British).
Standard deviations in parentheses

Table 2: Wave 1 Academic Inputs, Habits and Growth Mindset Scores

3.6 Growth Mindset

Growth mindset is measured with the questions in Dweck (2013). These questions have been used in different contexts and given consistent measurements of growth mindset. Students respond to the following statements in a Likert-scale format which ranges from strongly disagree to strongly agree with 7 choices:

- i) You can learn new things, but you can't really change your basic intelligence.
- ii) You have a certain amount of intelligence and you really can't do much to change it.
- iii) No matter how much intelligence you have, you can always change it a bit.
- iv) You can change even your basic intelligence level considerably.

Using the answers to these questions, a growth mindset scores is calculated (see appendix I for exact calculation). Table 2 shows the mean growth mindset scores for each demographic group. Female students have higher growth mindset scores than male students and this difference is significant at 1% significance level. There is no significant difference between ethnicity or age groups. Growth mindset is measured in wave 1 and wave 3.

3.7 Belief about the Returns to Study and Attendance

We elicit each student's subjective production function for academic performance by asking them to report their expected outcomes (measured in two ways – explained below) for the 9 combinations of private study set at 5, 10 and 15 hours per week with attendance at lectures and classes set at 60%, 80%, and 95% of all events. We first requested their expected mark (GPA, from 0 to 100) at each combination of input levels in a single grid, and then on a separate page for each input combination, their probability of attaining each of five degree classes (First, GPA$\geq$70; Upper Second, 60$\leq$GPA$<$70; Lower Second, 50$\leq$GPA$<$60; Third, 40$\leq$GPA$<$50; Fail, GPA$<$40) with these probabilities constrained to add up to 100%. Here we focus on probability of getting a first class degree and upper second class degree.

Wave 1

	First			Upper Second		
	Attendance			Attendance		
Study (pw)	60%	80%	95%	60%	80%	95%
5	13.06	17.27	21.68	23.03	29.59	26.94
	(17.13)	(19.46)	(22.29)	(17.48)	(18.45)	(17.23)
10	19.63	26.99	36.25	31.66	35.59	35.36
	(20.05)	(22.65)	(25.93)	(18.37)	(18.09)	(17.59)
15	30.62	40.85	52.24	34.96	36.11	32.24
	(24.73)	(25.73)	(26.92)	(17.15)	(16.77)	(17.53)

Wave 3

	First			Upper Second		
	Attendance			Attendance		
Study (pw)	60%	80%	95%	60%	80%	95%
5	15.88	19.16	24.01	28.51	31.59	32.22
	(18.44)	(19.96)	(22.8)	(19.18)	(18.82)	(19.28)
10	23.3	30.09	38.01	35.33	38.59	38.01
	(21.94)	(23.63)	(25.64)	(18.55)	(17.95)	(17.78)
15	34.7	44.75	54.88	38.02	37.14	32.6
	(25)	(25.11)	(26.74)	(17.82)	(17.35)	(17.71)

Table 3: Wave 1 and Wave 3 Conditional beliefs about academic performance

Table 3 shows descriptive statistics on the Wave 1 and Wave 3 distribution of the subjective production function. Note that the expected probability of attaining a First is increasing monotonically in attendance at all levels of study, and vice-versa. This is not true for the probability of attaining an upper second at the higher input levels, as the shift in students' probability distribution moves a greater mass into the higher degree class than is gained from lower degree classes.

4 Intervention

The treatment was delivered towards the end of the Wave 2 lab session. Students were sat in individual partitioned booths (so were unable to communicate with any other students) with their own computer screen and noise-cancelling headphones. Having completed a set of tasks designed to elicit several cognitive and non-cognitive traits, students were shown a 10-minute video followed by three multiple choice questions and up to 10 minutes to write a short text.

The students enrolled in BOOST were stratified by sex, age group, department, parental socio-economic status, and tariff quintile, and within these cells randomized into groups A and B. When invitations to sign up for a Wave 2 lab session were issued, each group was offered a different list of options (30 for each group, 2 each weekday at various times, for three weeks). Students asking to take part in a session they were not offered (but available to their friends) were told that because of one of the incentivized tasks involved competing against other participants, we wanted to minimize the chance of people who knew each other well being paired together, and this explanation was always accepted. The sessions were identical until the last section involving the video and subsequent incentivized tasks. Five students out of 1025 participants managed to defy their allocation and take part in the wrong session.

Group B students received the 'treatment' video. Screenshots from this treatment video are shown in Appendix II. They show that the video comprises a combination of images, visual text prompts, and short academic presentations.

The script contained the following messages: i) People's brains adapt and grow in response to learning opportunities. An example was given from a study showing the size of key parts of the brain increased following language training. ii) The structure and purpose of neurons, dendrites and synapses was explained. New imaging techniques show that the structure of a neuron is not fixed, and new dendritic spines can grow quickly. iii) This teaches us that we should think of the brain as a muscle: It grows with exercise. The more you challenge your brain to learn, retain and retrieve new information, the more dendritic spines you physically grow, the more you revisit the new connections you make, and the longer they will stay. An example of a study was given, showing that training one area of the brain using a computer game leads to improvements in other cognitive domains, that persisted for over one year. iv) Mistakes and challenges are really important for learning. Participants were told that when they are finding something difficult, it is not that you are reaching the limits of your ability, but an opportunity to train your brain to get stronger in that area by creating new neurons or new connections. An example was given from a study showing that brain activity highest after a mistake, but this is only true for those who believed that ability can grow. v) Finally, participants were told that a poor mark does not mean you they have low ability. They can train your brain to grow.

This was followed by information on practical implication of these lessons, that the most effective kind of study is where you challenge yourself. Four study tips were given relating to: 1) Self-testing, including writing notes, using flashcards, completing past papers, or using textbook questions, all of which are forms of active learning. More passive methods are only good for encoding information in memory the first time. 2) Spacing, with the message that study time on a particular topic is better distributed among several sessions. It last longer and more brain connections get formed. Material reviewed several times stays in the memory much longer. Cramming might feel effective but doesn't give the brain the opportunity to store information in long term memory. 3) Attending lectures and classes is effective especially complemented with note-taking and reading assignments. 4) Avoiding bad situations, since stress and lack of sleep inhibits formation of new brain cells and encoding of new information. Distractions like music or checking one's phone consume part of working memory so prevent encoding of information. In contrast, exercise improves blood flow to the brain.

Students were prevented from skipping ahead until they had spent 10 minutes on the page containing the video, though they could spend longer if they wished. They then were given 1 minute for each of three multiple choice questions, and rewarded with £1 per correct answer. They then had to spend at least two minutes, and up to 10 minutes on the task "Write a letter to a friend to explain that ability is not fixed and what implications this has for how he or she should study" They were rewarded with £1 per 200 characters (2 lines in the box they were shown to write in) of coherent text they wrote, up to a maximum of £10. These essays were reviewed (and number of lines counted) by a human member of the team, and incoherent text rejected.

Group A students received the 'control' video. Like the treatment video, it was entitled "What your brain can do", featured the same three talking heads; Steffan Kennett and Nick Cooper (Psychology, Essex) and Wandi Bruine de Bruin (Psychology, Leeds); had the same visual style, and lasted 10 minutes. Unlike the treatment video, it focused on the specialities of different regions of the brain, with evidence from studies showing the implications of damage to these regions. It contained no study tips, only information about which parts of the brain are being used when undertaking certain activities.

This was followed by three different multiple choice questions and the task "The brain is divided into different areas called lobes. Each lobe has several specific functions. Describe some of these functions and tell us where in the brain they are located. What happens when damage to the brain occurs? Give some examples by using the content of the video you have just watched or from other studies you might have come across", with the same timing and incentive structure.

We checked whether randomization worked for all the variables that we are interested in or not. Table 4 shows the difference in the stratification variables between those assigned to, and actually receiving, the treatment and control sessions. We do not find

	Group assignment			Group participation		
Variable	Control	Treatment	p-value (diff' in proportions)	Control	Treatment	p-value (diff' in proportions)
Female	0.513	0.515	0.911	0.589	0.592	0.903
Mature	0.072	0.077	0.671	0.081	0.072	0.589
High SES	0.372	0.378	0.838	0.356	0.334	0.402
Low SES	0.223	0.22	0.861	0.196	0.238	0.102
EU	0.155	0.155	0.992	0.222	0.202	0.436
Overseas	0.134	0.137	0.85	0.123	0.117	0.767
SES not classified	0.116	0.121	0.732	0.101	0.109	0.653
Tariff quintile:						
Missing	0.303	0.291	0.543	0.317	0.272	0.115
Lowest	0.134	0.144	0.519	0.139	0.145	0.777
Second	0.147	0.152	0.759	0.145	0.157	0.609
Middle	0.145	0.136	0.552	0.138	0.139	0.907
Fourth	0.129	0.131	0.9	0.121	0.142	0.331
Highest	0.142	0.147	0.755	0.142	0.147	0.85
N	978	979		496	530	

* significant at 10%, ** significant at 5%, *** significant at 1%

Table 4: Balancing Test on Stratifying Variables

any significant p-value in differences in proportions, so conclude that the randomization worked correctly on these stratifying variables.

Table 5 shows the differences in assignment to treatment and being actually treated in baseline measures of other, non-stratifying variables. Our analysis shows there is no significant difference between assignment to treatment or actually taking the treatment groups except the proportion of active learning. There are fewer observations in Table 5 than Table 4 because the randomization did not condition on participating in wave 1, where these baseline measures were collected.

5 Empirical Strategy

We investigate the impact of the intervention on growth mindset, academic achievement, academic inputs and study habits. Because our outcomes are likely to be autocorre-

	Group Assignment			Group Treatment		
Variable	Control	Treatment	p-value (diff' in proportions)	Control.	Treatment	p-value (diff' in proportions)
Growth Mindset	36.32	3.27	0.9232	36.55	36.8	0.6855
Attendance	0.52	0.56	0.8197	0.71	0.71	0.8977
Weekly Study	12.99	12.64	0.5646	13.29	12.76	0.4668
Active Learning	0.52	0.56	0.0030***	0.51	0.56	0.0021***
Cramming	0.41	0.39	0.6641	0.40	0.39	0.7878
Studying with Friends	0.22	0.20	0.2767	0.21	0.19	0.4011
Studying in the Same Place	0.78	0.75	0.1587	0.79	0.75	0.1528
N	637	636		437	460	

* significant at 10%, ** significant at 5%, *** significant at 1%

Table 5: Balancing Test on Academic Inputs and Habits

lated, we use an ANCOVA specification (McKenzie, 2012). We estimate the following equation:

$$y_{it} = \beta_0 + \beta_1 y_{it-1} + \beta_2 X_i + \beta_3 Treatment_i + e_i$$

where y_{it} is the post-treatment outcome of interest, y_{it-1} is the baseline outcome of interest, X is a vector of stratifying variables (gender, age, department, tariff quintile and ethnicity/SES group) and treatment is a dummy variable that takes the value of 1 if the student has taken the treatment and 0 if the student has not taken the treatment. The use of stratifying variables when checking the effect of an intervention is recommended in Bruhn and McKenzie (2009).

McKenzie (2012) argues that when there is high autocorrelation between variables before and after the intervention, one should use ANCOVA or differences-in-differences rather than post-treatment analysis and always needs to include at least one baseline. Bruhn and McKenzie (2009) also show that power improvements from stratified randomization are highest when autocorrelation is high. And they argue that if the total sample is fixed ANCOVA should be used.

As we do not have baseline grades for the students due to the fact that students take their exams in the summer revision period even for those who they take in the fall term, we use tariff scores of the students as our baseline measure of educational achievement. And as we do not have baseline measure for spacing out, we cannot use the above equation. We will use the method of post-treatment analysis as we do not have a baseline measure and will control for the stratification variable. The representation of the variables is same with those in the ANCOVA method.

$$y_{it} = \beta_0 + \beta_1 X_i + \beta_2 Treatment_i + e_i$$

6 Results

We use a subsample of British students to check the effect of the intervention. We exclude EU and overseas students for two reasons. First, these will be positively selected as these students put more effort and invest financially more in education; Second they do not have tariff scores which we use as the baseline for academic achievements. As we do not have any other measure for previous academic achievement, we would not be able to check the effect for these students.

6.1 Effect of the Intervention on Growth Mindset

Table 6 shows the effect of the intervention on growth mindset scores and growth mindset categories. The intervention increased the students' growth mindset scores for the whole sample. It increased the growth mindset score by 2.3 points and this effect is significant at 1%. This increase is equal to 25% of the standard deviation. We find that the intervention increased the female students' growth mindset scores by 2.12 points

	All	Female	Male	All	Female	Male
	Growth Mindset Score (Wave 3)			Growth Mindset Category (Wave 3) (Marginal Effects)		
Treatment	2.234***	2.120**	2.033*	0.071***	0.073**	0.060*
	(0.703)	(0.877)	(1.195)	(0.022)	(0.028)	(0.035)
Growth Mindset Score (Wave 1)	0.515***	0.489***	0.546***			
	(0.038)	(0.050)	(0.064)			
Growth Mindset Category (Wave 1)				0.157***	0.174***	0.140***
				(0.015)	(0.021)	(0.023)
Female	-1.901**			-0.053**		
	(0.807)			(0.025)		
High SES			*Base level*			
Low SES	1.059	1.588*	0.211	0.020	0.038	-0.006
	(0.788)	(0.960)	(1.375)	(0.025)	(0.032)	(0.039)
SES missing	0.707	-1.117	2.236	0.013	-0.037	0.048
	(1.055)	(1.420)	(1.688)	(0.034)	(0.039)	(0.055)
Age Code	0.630	1.924	-0.153	0.015	0.038	-0.016
	(1.719)	(2.263)	(2.759)	(0.055)	(0.076)	(0.080)
Constant	17.005***	13.607***	16.290**			
	(4.050)	(5.154)	(7.805)			
N	520	290	230	520	290	230
R-sq	0.312	0.357	0.326			
Department Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tariff Quintile Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Effect of the Intervention on Growth Mindset

and this is significant at 5%, it increased the male students' scores by 2.03 points but this is significant only at 10%. This shows that the intervention has a heterogeneous effect.

We find similar results for the growth mindset categories. We find that the intervention increased the propensity of belonging to the group of growth mindset by 7%. We find the heterogenous effect in the growth mindset category too. We find that the intervention increased the propensity for female students by 7.3% while it increased for male students by 6% but the effect for the male students is significant only at 10% significance level.

6.2 Effect of the Intervention on Educational Achievements

When we check the effect of the intervention on educational outcomes, we look for 3 type of outcomes: first year grade point averages, first year average exam grades and first year degree classes. As we do not have baseline variable for these variables due to the fact that the university administrates all the exams in summer revision period even though some courses are taken only in fall semester, we use their tariff scores as their baseline scores. the first two columns of Table 6 show the results for the academic outcomes; final grade and exam grade. Column 3 of the Table 6 shows the marginal effect of the intervention on getting a grade above 70 (classified as first class honors degree).

We find that the intervention increased the students' GPA by 1.89 percentage point (17% of a standard deviation). We do not find any difference between male and female students. We then checked the effect on the exam scores. We find that the effect is 1.55 percentage points increase but this effect is significant only at 10%. We find that the propensity of getting a higher degree class is affected by the treatment by 5.7%.

Hence, we have shown that our treatment increased both growth mindset and their academic performance. We now seek to investigate the mechanisms behind this reduced-form relationship.

6.3 Effect of the Intervention on Academic Inputs

We classify attendance, weekly study hours and proportion of weekly study hours spent on active studying as the academic inputs. When we check the effect of the intervention

	Grade	Exam	Honors ME
Treatment	1.888**	1.550*	0.057**
	(0.821)	(0.835)	(0.022)
Tariff	0.019***	0.014***	0.001***
	(0.005)	(0.005)	(0.000)
Tariff_M	2.740	2.427	0.100
	(3.019)	(3.115)	(0.079)
Female	0.801	0.802	0.036
	(0.927)	(0.943)	(0.025)
High SES		*Base level*	
Low SES	-1.997**	-1.480	-0.051**
	(0.923)	(0.936)	(0.024)
SES missing	-0.670	-0.720	-0.018
	(1.202)	(1.222)	(0.033)
Age_Code	0.568	-0.456	-0.015
	(1.949)	(2.030)	(0.053)
Constant	53.754***	54.106***	
	(4.547)	(4.734)	
N	681	670	685
R-sq	0.141	0.151	
Department Dummies	Yes	Yes	Yes

* significant at 10%, ** significant at 5%, *** significant at 1%

Table 7: Effect of the Intervention on Educational Achievements

on the academic inputs, we look for the effect on both spring term and summer term. As the summer term is shorter and includes only revision classes, but is also the period where they actually take the exams, the effect on summer term may be distinct from spring term for weekly study hours and active learning. Table 8 shows the ANCOVA results for academic inputs.

We find that the intervention increased the students' spring term attendance by 1.6 percentage points but this effect is significant only at 10%. We do not find any effect of the intervention on summer term attendance either. In the university, students need to tap their registration card to attendance card readers before each lecture to record their attendance. This is a way for the university to check the students' attendance and report any persistent absenteeism to the Home Office in line with the university's international student license. In the UK, all international students have to attend their courses and once they fail to attend a certain number of lectures and classes, their visas are curtailed and they cannot continue to their education. As this is not a concern for the British students, we cannot rule out the possible scenario where they do not carry or they lost their student cards and so they do not tap their cards to the reader.

We find that the intervention had a negative effect on the weekly study hours in summer term. Students study 4.64 hours less in a week due to the intervention and this effect is larger for male students. When we check age group heterogeneity, we found that mature students are not affected from the intervention but considering the low number observation in mature group, we cannot conclude that the intervention did not work for them. We do not find any effect of the intervention on spring term weekly study hours.

Lastly, we check the proportion of weekly study hours spent on active learning. We find that treatment had a positive effect on the proportion of active studying and the effect size is 9.6 percentage point (46% of a standard deviation). Similar to weekly study hours, we find no effect on the spring term active learning.

With these two findings, we can conclude that our intervention made the students more effective as they study less but in a more active way. This is one possible mechanism through which the intervention improved the students' academic outcomes.

6.4 Effect of the Intervention on Academic Habits

We check the effect of the intervention for both wave 3 and wave 4 measurements for cramming, studying with friends and studying in the same place as these are more likely

	Attendance		Weekly Study		Proportion Active Learning	
	Spring	Summer	Spring	Summer	Spring	Summer
Treatment	0.016*	-0.001	0.339	-4.642***	-0.066	0.096**
	(0.009)	(0.018)	(0.913)	(1.767)	(0.072)	(0.047)
Attendance Autumn	0.959***	0.806***				
	(0.028)	(0.056)				
Study (wave 1)			0.410***	0.424***		
			(0.043)	(0.084)		
Prop'n Active (wave 1)					1.129***	0.408***
					(0.177)	(0.113)
Female	0.022**	0.073***	2.160**	5.077**	-0.026	0.050
	(0.010)	(0.021)	(1.056)	(2.001)	(0.082)	(0.052)
High SES				Base level		
Low SES	-0.003	-0.015	-1.338	-0.309	-0.111	-0.019
	(0.010)	(0.021)	(1.018)	(1.964)	(0.081)	(0.052)
SES missing	0.002	-0.034	-1.678	-4.619*	-0.047	0.121*
	(0.014)	(0.027)	(1.365)	(2.694)	(0.109)	(0.071)
Young	0.001	0.019	-0.538	0.274	0.088	0.143
	(0.022)	(0.044)	(2.222)	(4.737)	(0.171)	(0.122)
Constant	-0.088*	-0.111	7.738	20.045*	-0.070	-0.414
	(0.052)	(0.104)	(4.919)	(10.271)	(0.385)	(0.268)
N	672	672	514	471	490	450
R-sq	0.689	0.399	0.218	0.146	0.141	0.129
Department Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tariff Quintile Dummies	Yes	Yes	Yes	Yes	Yes	Yes

* significant at 10%, ** significant at 5%, *** significant at 1%

Table 8: Effect of the Intervention on Academic Inputs

to change depending on the students' location, whether they study back in their family's house or on campus. Table 9 shows the treatment effects for on these habits habits.

We do not find any effect of the intervention on cramming in wave 3 or wave 4. When we check heterogeneity, we find a larger treatment effect for Black British students, becoming more likely to cram in wave 3, but this difference diminishes in wave 4. It might be that students in the revision period cram a lot due to having several exams in the period. If we had information about their cramming behavior right before their coursework deadlines, we would be able to get a more consistent measurement of the cramming behavior as they generally have a more distributed schedule for their coursework. But as all of the exams are in one period, they might be more likely to cram for the courses that they feel that they are better.

We find that there is a negative effect of the intervention on studying with friends in wave 3 but this effect is significant only at 10%. We also find that white low SES students are less likely to study with their friends in wave 3 and this is significant at 5%. But these effects diminish in wave 4. In wave 4, we find that bottom quintile students are now less likely to study with their friends and this is significant at 5%. A limitation of this variable is that we do not know why and how they study with their friends. They may consider studying with their friends as peer support and they may collaborate, but this may also be disruptive. This contradiction may rule out the possible effect of the intervention.

We find no effect of the intervention on studying in the same place in wave 3 or in wave 4. Considering some students are working better in the library than anywhere else or some students work with their friends, due to the fact that the library and the group study rooms are more crowded in the summer revision period than autumn and

	Cramming		Studying with friends		Studying in the same place		Spacing
	Spring	Summer	Spring	Summer	Spring	Summer	Summer
Treatment	0.035	0.010	-0.057*	-0.016	-0.012	-0.040	0.116***
	(0.042)	(0.045)	(0.034)	(0.040)	(0.036)	(0.039)	(0.037)
Cramming	0.270***	0.285***					
(Autumn)	(0.042)	(0.045)					
Study with friends			0.301***	0.237***			
(Autumn)			(0.033)	(0.045)			
Study in same place					0.239***	0.215***	
(Autumn)					(0.035)	(0.040)	
Female	-0.001	-0.010	0.036	0.008	0.071*	-0.012	-0.013
	(0.048)	(0.049)	(0.040)	(0.045)	(0.040)	(0.044)	(0.042)
High SES				*Base level*			
Low SES	0.011	0.012	-0.051	0.001	-0.059	-0.000	-0.009
	(0.047)	(0.049)	(0.038)	(0.044)	(0.041)	(0.043)	(0.042)
SES Missing	0.025	0.062	-0.029	-0.008	-0.076	-0.073	0.011
	(0.066)	(0.075)	(0.051)	(0.061)	(0.055)	(0.064)	(0.057)
Young	0.102	-0.050	0.220**	0.011	0.015	-0.135	-0.186
	(0.110)	(0.117)	(0.101)	(0.105)	(0.087)	(0.117)	(0.121)
N	390	353	509	470	520	472	471
Department Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tariff Quintile Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* significant at 10%, ** significant at 5%, *** significant at 1%

Table 9: Effect of the Intervention on Academic Habits

spring semester, this might not show the real effect of the intervention. Space constraints might play an important role in wave 4.

Lastly, we check the spacing out behavior. We find that treated students are more likely to space out their study on a particular topic. Female students are found to be affected more than male students and white high SES students are found to be affected more than any other SES groups.

6.5 Effect of the intervention on the beliefs about the production function

Table 10 shows the effect of the intervention on the belief of getting different degree classes conditional on attendance and weekly study hours. As we have 9 different attendance and weekly study hours combinations for each respondent, we pool these and cluster standard errors at the individual level.

We find that treatment has a positive and significant effect on the belief that student will get an upper second degree class and on the belief that student will get an lower second degree class conditional on the weekly study hours and attendance, holding constant both the student's baseline expectation and their hours of study and per cent attendance. We also find a negative effect of the intervention on the belief that students would get a third class degree (considered a very poor outcome) conditional on study hours and attendance. When we look at the good degree class, which is first and upper second, we also find a positive effect of the intervention. The intervention increased the students' probabilistic beliefs that they would get a good degree conditional on study hours and attendance by 1.31 percentage points (4.3% of a standard deviation).

The zero coefficients shown on attendance and study show there is no change in the perceived value-added of these inputs in students' subjective production technologies between autumn and spring. This is fully accounted for by the baseline conditional expectation. The positive treatment effect on expected outcomes however shows that the underlying subjective production technology has become significantly different for the treated students.

Spring (wave 3) expectations:	Pr(First class)	Pr(Upper 2nd)	Pr(Lower 2nd)	Pr(3rd)	Pr(First/Upper 2nd)
Treatment	0.189	1.238***	1.824***	-1.233***	1.312**
	(0.481)	(0.371)	(0.432)	(0.477)	(0.636)
Baseline (wave 1) expectations:					
Pr(First class)	0.460***				
	(0.009)				
Pr(Upper 2nd)		0.348***			
		(0.012)			
Pr(Lower 2nd)			0.314***		
			(0.012)		
Pr(Lower 2nd)				0.343***	
				(0.011)	
Pr(First/Upper 2nd)					0.475***
					(0.009)
Conditional on inputs:					
Attendance, %	-0.000	-0.000	0.000	0.000	-0.000
	(0.017)	(0.013)	(0.015)	(0.016)	(0.022)
Study Hours, per week	0.000	-0.000	-0.000	0.000	0.000
	(0.058)	(0.045)	(0.052)	(0.058)	(0.077)
Female	2.413***	-0.118	0.542	0.010	2.295***
	(0.546)	(0.420)	(0.492)	(0.542)	(0.722)
High SES			*Base level*		
Low SES	-1.477**	0.787	0.368	-0.582	-0.982
	(0.661)	(0.509)	(0.594)	(0.656)	(0.874)
SES unclassified	3.054***	3.130***	-1.239**	-0.635	6.104***
	(0.680)	(0.523)	(0.611)	(0.674)	(0.899)
Young	6.163***	-1.210*	-3.913***	-1.285	5.025***
	(0.920)	(0.707)	(0.830)	(0.911)	(1.215)
Constant	13.497***	33.875***	34.984***	20.112***	40.725***
	(2.579)	(2.052)	(2.389)	(2.557)	(3.477)
N	7317	7317	7317	7317	7317
R-sq	0.331	0.145	0.171	0.177	0.303
Department Dummies	Yes	Yes	Yes	Yes	Yes
Tariff Dummies	Yes	Yes	Yes	Yes	Yes

* significant at 10%, ** significant at 5%, *** significant at 1%

Table 10: Effect of the Treatment on conditional beliefs about academic performance

7 Conclusion

In this paper, using new data from first year students at a research-intensive university, we look at the effect of a light-touch growth mindset and study habits intervention. We find that our intervention increased the students' growth mindset scores. It also increased the grades of the students and their propensity to get a higher degree class. It also decreased the weekly study hours but increased the proportion of study hours spent on active studying. It affected attendance positively but only at 10% significance level. We also check the effect of the intervention on academic habits such as cramming, studying in the same place, studying with friends and spacing out. We find that there is no effect of the intervention on cramming, it decreases the propensity to study with friends in wave 3 but this effect diminishes in wave 4 and it increases the spacing out behavior. We also show that the intervention increased students' expectations of their performance conditional on fixed levels of educational investments, meaning their underlying subjective production function has changed.

Overall, the intervention increased students' grades, while making them study less but using a greater concentration of active learning methods. This resulted in a given hour of study time becoming more productive.

Our findings extend the existing literature in several ways. In line with the extant research we have presented an intervention that successfully inculcates a growth mindset in a cohort of undergradate students, but have also shown a positive effect on students' academic outcomes in assessments concluded five months later, and shed important light on the mechanisms for these effects. Treated students adapted their study methods to consume less time overall, but spent in a more effective way, both in terms of active learning methods and spacing out of study on particular topics, in accordance with understanding of the effective encoding of information in long-term memory.

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Appendix I: Growth Mindset Score Calculations and Categories

Growth mindset is measured with the questions in Dweck (2013). The questions are:

i) You can learn new things, but you can't really change your basic intelligence.

ii)You have a certain amount of intelligence and you really can't do much to change it.

iii) No matter how much intelligence you have, you can always change it a bit.

iv) You can change even your basic intelligence level considerably.

The answers to these questions are in Likert-scale which range from strongly disagree to strongly agree with 7 choices. Then using the answers to these questions, growth mindset scores are calculated as follows:

Strongly Disagree (0 pt), Disagree (1 pt), Somewhat Disagree (1.25 pt) Neutral (1.5 pt) Somewhat Agree (1.75 pt) Agree (2 pt) Strongly Agree (3 pt)

The first two questions are reverse coded while the last two questions are normal coded. The calculation of the growth mindset score then is

Growth Mindset Score=5*(3-gm1+3-gm2+gm3+gm4)

There are 4 different categories of growth mindset based on this score.

i) If someone scored below 22, then this student is classified as having strong fixed mindset.

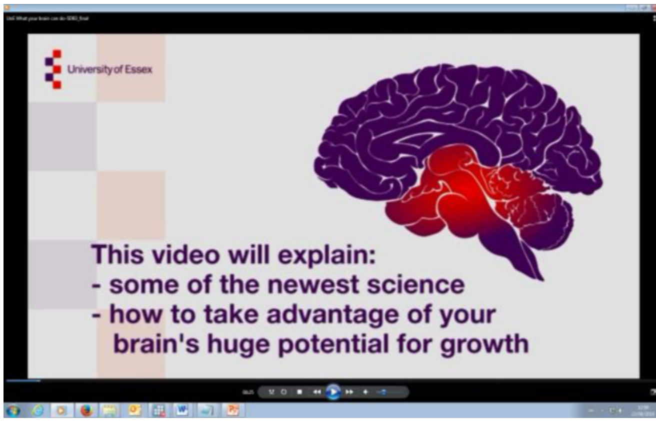
ii) If someone scored between 22 and 34, then this person is classified as having fixed mindset with some growth ideas.

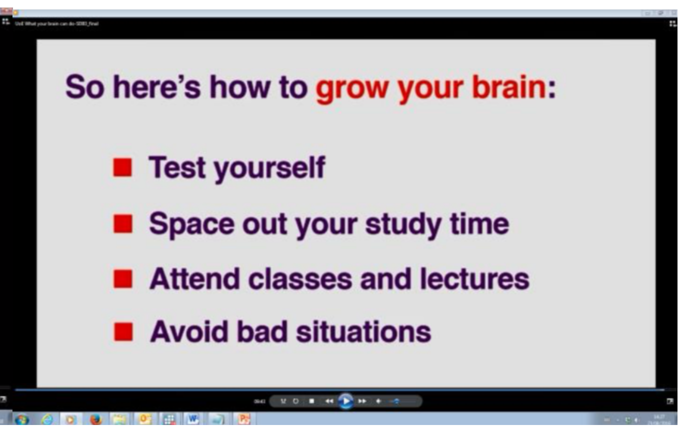
iii) If someone scored between 35 and 44, then this person is classified as having growth mindset with some fixed ideas.

iv) If someone scored above 44, then this person is classified as having strong growth mindset.

Appendix II: Screenshots from the Intervention

Sample images from treatment video





Sample images from control video