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Abstract

We analyze the relation between time preferences, study effort, and academic performance among first-year business and economics students. Time preferences are measured by stated preferences for an immediate payment over larger delayed payments. Data on study efforts are derived from an electronic learning environment, which records the amount of time students are logged in, the number of exercises generated, and the fraction of topics completed. Another measure of study effort is participation in an online summer course. We find no statistically significant relationship between impatience and study effort. However, we find that impatient students obtain lower grades and fail final exams more often, suggesting that impatient students are of lower unmeasured ability. Impatient students do not seem to have severe selfcontrol problems, as they do not earn significantly fewer study credits, nor are they more likely to drop out as a result of earning fewer study credits than required.

JEL-Code: D030, D900, I210.

Keywords: time preferences, education, study effort, academic performance.

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1 Introduction

People are often confronted with the choice to take a costly action now in order to obtain a benefit in the future. Although people generally tend to attach less weight to future outcomes than to present outcomes, there is substantial heterogeneity in how individuals behave in those kind of situations. It has been found that experimental measures of individuals' time preferences correlate with their alcohol consumption, smoking behaviour, body mass index (Borghans and Golsteyn, 2006; Chabris et al., 2008; Sutter et al., 2013), and credit card borrowing (Meier and Sprenger, 2010). Differences in individuals' time preferences may also help to explain the extent to which individuals are successful in education. Ultimately, being successful in education requires putting in effort. Individuals' choice of effort typically involves an intertemporal trade-off: effort costs of studying an additional hour are incurred immediately, while the benefits materialize in the future. We might therefore expect that impatient individuals exert less effort, resulting in lower educational attainment and performance. This hypothesis holds true regardless of whether one thinks of impatient individuals as exhibiting high exponential discount rates, or as strong hyperbolic discounters, reflecting a self-control problem.[1]

A number of recent papers find evidence in line with this hypothesis. Kirby et al. (2005) find that, in a sample of undergraduate students of two American colleges, impatient students have significantly lower grade point averages. Cadena and Keys (2015), using panel data representative of the US population, show that individuals who are classified as impatient by their interviewer, are more likely to drop out from high school and from college. Lavecchia et al. (2015) exploit the same data to show that students classified as impatient report spending fewer study hours. Golsteyn et al. (2014) link individuals' time preferences measured at age 13 with several outcomes in later life, up to 40 years later. They conclude that individuals who make impatient choices at age 13 obtain lower grade point averages in compulsory school and high school, and are less likely to graduate from both high school and university. De Paola and Gioia (2013) find that, in a sample of Italian university students, impatient students obtain lower grades, while they find no differences in the number of study credits earned three years after enrollment.

[1] The model we have in mind is that individuals trade off future benefits and present costs. In terms of the β/δ model (Laibson 1997), future benefits are discounted by $\beta\delta^t$, where β reflects a self-control problem and δ is a time-invariant discount factor. The theoretical prediction is therefore that impatient individuals study less, regardless of whether impatience is captured by a low δ or a low β. Making the distinction between β and δ would be highly relevant from a policy perspective, as the existence of self-control problems increases the scope for welfare improving policy interventions. Our measure of time preferences does not distinguish between the two, as reliable measurement of time inconsistent preferences is difficult (Dohmen et al. 2012).

In this paper, we contribute to this literature by investigating the relation between time preferences, study effort, and academic performance. In contrast to previous studies, we explore data on actual study efforts rather than analyzing data on study outcomes only.[2] We collect information on study efforts of 766 first-year business and economics students for an obligatory course in quantitative methods. An interesting feature of this course is that students are supposed to practice the course material in an electronic learning environment, which automatically records for each student the amount of time logged in, the number of exercises generated, and the percentage of topics completed without help of the electronic assistance tools. We use this information as measures of study effort. We further measure effort by voluntary participation in an online summer course that addresses deficiencies in basic mathematical skills. We measure performance in the course in quantitative methods by the final exam grade and whether this grade was sufficient to pass the course. We do not have information on study effort in other courses, but our effort measures predict performance in other courses just as well as in the quantitative methods course. To investigate how impatience relates to first-year academic performance more broadly, we use four different performance measures. The first two are based on final exam performance in other first-year courses: the average grade obtained (excluding results obtained in re-examinations) and the number of final exams failed in the first attempt. The other two capture study progress: the number of study credits obtained during the first year (i.e. the number of courses passed weighted by the number of study credits assigned to each course), and whether students fulfill the university's minimum requirements for first-year performance. Specifically, failing too many courses or both first-year courses in quantitative methods leads to exclusion from the study program. Failing the exam in quantitative methods may therefore have serious consequences. We measure time preferences by a survey question that confronts students with three hypothetical choices between an immediate payment of €1000 or a larger delayed payment, the respective amounts being €1100, €1050, and €1250.[3]

By analyzing students' actual study efforts, we provide direct evidence on the existence of a causal relationship between time preferences and academic performance. Establishing causality is challenging if not impossible, as there is typically no exogenous variation in time preferences that can be exploited. A promising alternative strategy is therefore to investigate the channel underlying the relation between time preferences and academic

[2] A noteworthy exception is the evidence provided by Lavecchia et al. (2015) in their survey of the literature on behavioral economics of education. An important difference is that they use self-reported data, whereas we use data from an electronic learning environment.

[3] Falk et al. (2013) show that non-incentivized survey measures of time preferences are highly correlated with incentivized measures of time preferences.

performance, namely whether and to what extent impatient students actually exert less effort. This yields direct evidence on how time preferences influence study behavior, which is important as study outcomes may be correlated with time preferences for other reasons than study effort.

We find little support for the hypothesis that impatient students actually exert less effort. We find no statistically significant differences in the amount of time students are logged in, the number of exercises generated, and in summer course participation. Although the effects are generally imprecisely estimated, the point estimates are consistently close to zero. However, in line with findings of previous studies, we find that impatience is associated with weaker academic performance. Impatient individuals obtain lower final exam grades, and fail a final exam more often. In particular, students who always prefer the immediate payment are estimated to fail 31% more final exams than students of similar ability, amounting to 0.5 additional failed final exam per academic year. Taking into account that impatience may also affect performance via a reduction in the skills and knowledge students possess at the start of the academic year, the cumulative effect of impatience may be as large as 44%. These effects are mainly driven by relatively able students, as measured by their score on an entry test.

The most plausible explanation for this paradoxical result is that impatient students are of lower unmeasured ability. Consistent with this interpretation, we find that impatience is negatively correlated with measures of ability. Although our measures of ability (score on an entry test and prior education) arguably reflect accumulated knowledge, several existing studies also report negative correlations between impatience and measures of intelligence that are closer to innate ability (Frederick, 2005, Shamosh and Gray, 2008, Dohmen et al., 2010). An alternative explanation for this paradox is that impatient students have a less effective learning style, for which we find some indications in the data. In any case, our findings suggest that differences in academic performance cannot simply be attributed to differences in effort. Rather, they suggest that standard measures of impatience are associated with other, hard to observe factors that are relevant for performance.

The negative association between impatience and final exam results does not carry over to measures of study progress. Correcting for ability, we do not find that impatient students obtain significantly fewer study credits during the first year, nor are they less likely to fulfill the university's minimum performance requirements. This suggests that impatient students do not suffer from *severe* self-control problems. If they had severe self-control problems, we might expect that they also earn fewer credits during the first year, and that they are less likely to meet the university's performance requirements. Although this finding goes against the hypothesis that impatient students show weaker performance, it can easily be reconciled with impatient time preferences: impatient students arguably find study delay more problematic. Moreover, their relatively good performance in the resit exams is also consistent with their time preferences, as impatient students may prefer postponing their study effort to the resit exam.

Our findings are well in line with the results of De Paola and Gioia (2013), who find that impatience is reflected in lower grades, but not in higher dropout rates or fewer study credits. However, our results stand in contrast to the results of Cadena and Keys (2015) and Golsteyn et al. (2014), who find that impatience is associated with important life-lasting consequences, such as higher dropout rates and lower educational attainment. Moreover, Cadena and Keys (2015) report substantial evidence for dynamically inconsistent or impulsive behavior. Lavecchia et al. (2015) provide additional evidence by showing that impatient students report spending less time on their homework. A likely reason for those diverging findings is that Cadena and Keys (2015), Lavecchia et al. (2015), and Golsteyn et al. (2014) investigate representative samples of the general population, whereas both De Paola and Gioia (2013) and we concentrate on university students. Arguably, time preferences have more dramatic effects on behavior in the general population, as more intelligent individuals, like university students, may have developed effective ways to curb impulsive tendencies, or may be better able to foresee the possible consequences of impatient behavior.[4]

Our paper also relates to a recent literature on procrastination and self-control. De Paola and Scoppa (2015) show that students who procrastinate completion of the university enrolment procedure have lower educational achievement, and that remedial courses designed to improve basic learning skills were particularly effective for procrastinators. Duckworth et al. (2012) emphasize the role of self-control in predicting the development of middle school grades (see also Duckworth and Seligman, 2005, and the references therein). Moffit et al. (2011) show that self-control in childhood is associated with a wide array of important life outcomes, such as income, health, and criminal convictions. A related strand of literature analyzes the demand for commitment devices, and their effectiveness in overcoming problems of self-control, see e.g. Ariely and Wertenbroch (2002).[5] The difference between those studies and ours is that we investigate time preferences rather than self-control problems. Time preferences describe how individuals make intertemporal trade-offs assuming rational decision making, while the concept of self-control assumes that individuals sometimes fail to make the choices they find optimal from an ex-ante perspective. Although the distinction is

[4] Alternatively, the distribution of time preferences may be much wider in the total population. However, Andersen et al. (2010) compare time preferences in a sample of university students with those in the general population, and find that the distributions do not differ that much.

[5] There is also a recent literature on the effectiveness of financial incentives in improving study behavior and outcomes, see Lavecchia et al. (2015) for an overview. The idea is that financial incentives offset immediate costs of studying with immediate benefits.

theoretically clear and highly policy relevant, it is hard to distinguish the two in practice, as measures of time preferences arguably also reflect impulsive tendencies.[6]

The paper proceeds as follows. First, we describe the background of our study and the data used in the analysis. Then, in section 3, we present the main analysis and results, including some robustness checks. In section 4, we discuss possible interpretations of our results. Section 5 concludes.

2 Data description

2.1 Background

Our sample consists of all first-year students enrolled at the start of the academic year 2012-2013 at the School of Business and Economics of Maastricht University. We collected data on their study behaviour during an introductory course in quantitative methods, abbreviated as QM1. This course is obligatory for all students who are enrolled at the School of Business and Economics of Maastricht University and takes place the first period of the academic year.[7] The course has a special place in the curriculum. Students enrolled at the School of business and economics are required to obtain at least 34 out of 60 course credits in their first year, and in addition pass at least one of the two courses in quantitative methods offered in the first year. Students who fail to meet those criteria receive a so-called 'negative binding study advice' (BSA), implying that they have to abandon their study program, and are excluded from the study program for six years.[8] Hence, students face strong incentives to pass this course.

The course consists of 7 weeks of lectures and tutorials, followed by a written exam. The aim of the course is to provide students with a basic understanding of mathematics and statistics. Attendance of lectures is not obligatory. Tutorials at Maastricht University are organized according to the principles of problem-based learning, which involves intensive collaboration in small groups of students to solve unstructured, often open-ended, problems. Students are supposed to take the lead in discussing the problems, while the teacher has a facilitating role, see Wilkerson and Gijselaers (1996)

[6] Burks et al. (2012), Dohmen et al. (2012), and Reuben et al. (2015) find that time preferences as measured by financial decision making correlate with procrastinating behavior. In fact, Dohmen et al. (2012) find that elicited discount rates predict better than measures of time-inconsistent preferences. On the other hand, Wölbert and Riedl (2013) find that elicited discount rates do not correlate with self-reported measures of impulsivity.

[7] The first block consists of seven weeks of education, starting September 3, followed by an exam October 27. The resit exam took place 11 January.

[8] In addition to this requirement, students have to pass all first-year courses within two years. All universities in the Netherlands have similar regulations, although the exact performance requirements differ by university and faculty.

for a detailed description. Tutorial groups are therefore small (at most 14 students), the tutor being either a staff member or a teaching assistant. Students are required to attend at least 7 out of 9 tutorials.

The exam consists of 40 multiple choice questions. Students who fail the exam have the opportunity to retake the exam two months later, after the Christmas holidays. Students who passed the final exam are not allowed to participate in the resit.[9] Students had the opportunity to acquire a bonus of at most 20% of the maximum score in the final exam. This bonus depends on their performance in three midterm tests, administered on the computer, and the fraction of exercises completed in the electronic learning environment. By completing more exercises, students partially compensate for a less than perfect score on the midterm test. Final exam grades are always expressed on a scale 1 (lowest) to 10 (highest), where 5.5 is the minimum grade required to pass the exam. The final passing rate in our sample is 93%, and 77% of students pass after the first attempt.

A special feature of this course is its use of an electronic learning environment, MyLab, which accompanies Pearson's textbooks in mathematics and statistics.[10] Students are supposed to use MyLab to practice the course material and prepare for the midterm tests. Every week, students are supposed to solve a set of problems related to the topics covered in that week. Each topic is introduced by a test problem to assess existing skills and knowledge. Students who master the material will solve the problem, and move on to the next topic. Students who do not fully master the material may ask for assistance that guides them to the correct solution ("help me solve this"), or for a step-by-step worked example ("view an example"). Students will continue receiving similar problems until they are able to solve them without the use of the assistance tools. When they succeed, they automatically move on to the next topic. Students who do not manage to solve the problem without use of the electronic assistance tools may decide to move on to the next topic manually. Students who completed all topics, but nevertheless feel that they need additional practice, can restart a topic, in which case MyLab provides new, similar exercises. A topic is considered completed when a student managed to solve the problem without help of the electronic assistance tools at least once. So, all students deal with the exact same topics, but students differ in the number of exercises, and hence time needed, to com-

[9] Ambitious students who care about obtaining a high grade may therefore strategically not show up or deliberately fail the first exam in order to take the resit exam. By doing so, they have more time to prepare and hence obtain a higher final grade. To the extent that patient students are more prepared to do so, we underestimate the effects of impatience on first exam performance. However, we do not find that patient students obtain higher grades in the resit.

[10] Pearson offers MyLab applications in several disciplines. The course Quantitative Methods 1 uses mathematics and statistics applications, named MyMathLab and MyStatLab, respectively. See http://www.mymathlab.com and http://www.mystatlab.com for further information.

plete each topic, as well as the number of topics completed, and the number of additional exercises after a topic has been completed. MyLab records the fraction of topics completed, the total number of exercises provided, and the amount of time each student is logged in. The system automatically logs off after 30 minutes of inactivity. Furthermore, MyLab records how often students ask for assistance in the form of guided solutions ("help me solve this") and sample problems ("view an example"), which gives us insight in differences in learning style.[11] MyLab is an important course tool, as it provides a particularly good preparation for the midterm exams.

Other data were collected by means of a number of online questionnaires during the course period. Those questionnaires were mainly concerned with student motivation and learning styles.[12] In the final week of the course, students had to write an assignment in which they test whether their own responses differ significantly from the average response on a number of these questionnaires' items. Filling out these questionnaires was therefore a prerequisite to complete the assignment. As a result, all first-year students filled out these questionnaires. We measured risk and time preferences in the questionnaire administered in week 6 of the course.

2.2 Effort

Our first measure of effort is the total amount of time a student is logged in to the electronic learning environment, MyLab. The main advantage of this measure is its objective and precise measurement. The median amount of time spent in MyLab is about 8 hours per week. This is a substantial part of students' total study time, as they are supposed to spend 20 hours per week on this course, including obligatory attendance of 3 hours of tutorials. A potential limitation is that a student does not need to be active in MyLab during the time he is logged in: only after 30 minutes of inactivity a student is automatically logged off. We therefore also use information on the number of exercises generated by MyLab as a second measure of study effort. The two measures are highly related (pairwise correlation: 0.49), suggesting that students who are logged in are generally active during that time. The distribution of both effort measures are depicted in figures A3 and A4, respectively.

In order to get a complete picture, we also analyze the fraction of top-

[11] MyLab does not record all requests for sample problems, but only for the final attempt in a given topic. This makes the interpretation problematic: the more a student of a given ability practices, the less likely he is to request a sample problem in his final attempt. All requests for guided solutions, however, are recorded. For 29 students information on assistance requests was lost because their accounts were incidentally reused in later years.

[12] Students were informed that these data would remain confidential, and used in anonymous format for research purposes as well as improvement of QM1 education. Research using similar data from previous cohorts is described in Tempelaar et al. (2012, 2013a, 2013b).

ics completed in the electronic learning environment. As explained above, MyLab does not only record the amount of time spent, but also keeps track of the fraction of problems the student manages to solve without electronic assistance. This gives us some idea about whether students understood the course material.[13] Completing all topics is a matter of effort and ability. The exercises are constructed in such a way that it is not too hard to complete most of the topics, also because students can infinitely practice and ask for assistance when attempting to solve a problem. As a result, 25% of students complete all topics, and about half of our sample completes at least 98% of all topics.[14] The full distribution is shown in figure A5.

An inherent limitation of effort measures derived from the electronic learning environment is that we do not observe study efforts outside MyLab, for instance studying written course material or attending lectures. This is a problem to the extent that impatient students are more likely to study Mylab than written course materials, or to attend lectures.[15] This concern seems less relevant for our final measure of effort: participation in an online summer course that takes place each year during the three months preceding the start of the academic year. The university offers this course in response to increasing numbers of students that start their studies with a deficiency in mathematics. The course is advertised on the web page describing the economics and business study programs, and on a web page that offers practical information for prospective first-year students. Moreover, all students who receive their proof of admission are informed about the course by email. Participation is voluntary, but recommended for students who were on a high school track involving little mathematics, which is about 2/3 of our sample. Students can take a 10-15 minutes online entry test to identify deficiencies in their mathematical skills. The course takes about 80 hours of study, depending on pre-existing knowledge, and is entirely online.[16] In

[13] As MyLab records this information separately by problem set and subject (math and statistics), we sum the scores (i.e. the fraction of topics completed) obtained over the 7 weeks and rescale them to a 0-100% scale. This procedure is preferable to calculating the unweighted fraction of completed topics, i.e. dividing the sum of completed topics by the total number of topics. The reason is that the number and difficulty level of exercises differs by week and subject. Our procedure ensures that weeks with few, but difficult exercises get a higher weight.

[14] Many students complete most, but not all topics. The reason is that there are topics that require completing exercises that consist of several subquestions. A topic is only counted as completed when all subquestions are correctly solved without help of the electronic assistance tools. If one of the subquestions is incorrectly answered, students need go through the whole exercise again to complete the topic, i.e. solving a similar exercise consisting of a number of subquestions. Many students are not willing to do so, and therefore fail to complete one or a few exercises.

[15] As a robustness check, our questionnaire in week 6 asked students to indicate the average total number of hours spent on the course QM1 each week. As self-reported measures may suffer from potentially important biases, we do not present results using this measure. Results are qualitatively similar when we use this measure.

[16] For further information, see

2012, costs of participating were €50.

2.3 Performance measures

We collected information on students' performance in the course QM1, as well as information on performance in all other first-year courses. In case of QM1, we investigate two measures of performance: the final exam grade, and whether a student passed or failed the final exam. The grade distribution is shown in figure A6, where grades below 5.5 are insufficient to pass the exam. We do not consider results obtained in the resit exam, as it is cleaner to focus on the results obtained in the final exam: all students take the exact same test and have the same opportunities to prepare. Also, we do not have information on study efforts for the resit exam.

For all other first year courses, we have four measures of performance. In analogy with our performance measures in the course QM1, we investigate the grade point average (GPA), weighted by the number of study credits, of all final exams, as well as the number of final exams failed over the course of the first year. In both measures, we exclude results obtained in the resit. Further, we investigate the number of course credits (ECTS) obtained, and whether a student receives a negative binding study advice (BSA), i.e. drops out as a result of failing to meet the performance requirements explained above. The respective distributions are shown in figures A7-A9, and descriptive statistics are provided in Table 2.[17] We expect a negative relation between impatience and all of those performance measures, but we also expect some differences. Intuitively, we might expect that impatient students are willing to accept a higher risk of failing an exam, but that they are much less willing to do so if failing will lead to a negative binding study advice (BSA) or study delay (ECTS).

2.4 Time preferences

Data on time and risk preferences were collected by means of the online questionnaire that was administered in week 6 of the course.[18] Specifically, time preferences were measured with the following hypothetical question:

Suppose someone you **fully trust** offers you a gift of **€1000 today**. However, he tells you that you can wait for one year and receive **€1100** instead. Which would you prefer?

a) €1000 now

b) €1100 in a year from now

http://www.maastrichtuniversity.nl/web/Faculties/SBE/Theme/Departments/QuantitativeEconomics/Floating_Pages_QE/OnlinePreparatoryCourses.htm

[17] As can be seen from Table 2, 13% of the sample receives a negative BSA.

[18] As students did not take a final exam yet, we can rule out that their exam performance affects their revealed preferences.

This question was repeated two times, where the postponed amount was subsequently changed to €1050 and €1250. The idea behind those questions is that most individuals prefer the immediate payment when the delayed payment is low, but switch to the delayed payment when the latter amount is high enough. The amount for which individuals switch to the delayed payment is our measure of impatience. Hence, we can distinguish between individuals who always prefer the delayed payment (most patient), those who switch when the amount is €1100 or €1250, and those who always prefer the immediate payment (most impatient). Out of the 882 students who filled out our questionnaire, 20 students did not answer this question, while 7 individuals provided inconsistent answers, and are therefore dropped from the analysis.[19] We decided to use hypothetical payoffs rather than real monetary payoffs, because even with a sizeable budget the expected amount at stake would be limited to only a couple of euros. We do not think that when the stakes are so low, introducing real monetary payoffs would lead to more accurate measurement of preferences for present over future consumption, as consumption at any point in time will not be influenced by such low amounts. Falk et al. (2013) show that non-incentivized measures of patience strongly correlate with incentivized measures obtained in the lab (see Dohmen et al., 2013, for a similar result on a self-assessed measure of impatience).[20] A more important limitation of this measure is that it might be confounded by, for instance, mathematical ability. More able individuals might be better able to calculate implied discount rates, and may realize that they can earn an above-market rate for all delayed payments. This wil make more intelligent individuals appear as relatively patient. Important advantages of this measure are that similar measures have been used by closely related papers (Kirby et al., 2005, De Paola and Gioia, 2013, and Golsteyn et al., 2014), which facilitates the comparison with their results, and that they have been shown to correlate with several real-life behaviors (see in addition to the papers mentioned in the introduction, Dohmen et al., 2012).[21] Moreover, it is conceptually clear what it measures: the question is well defined, which is less clear for subjective measures.

[19] Answers are considered as inconsistent when an individual prefers the postponed payment when this amount is relatively low, while preferring the immediate payment when the postponed payment is even larger.

[20] Incentivizing the measurement of time preferences is common in lab experiments (e.g. Kirby et al., 2005; Dohmen et al., 2010; Castillo et al., 2011; Sutter et al., 2013), but uncommon in surveys (e.g. Cadena and Keys, 2015; De Paola and Gioia, 2013; Golsteyn et al., 2014).

[21] Empirical results for measures of time inconsistency, i.e. declining or increasing discount rates revealed when the time horizon is varied, are more mixed (Dohmen et al. 2012). We therefore decided to concentrate on the discount rate as a measure of time preferences, and take an agnostic stance on whether this reflects time inconsistency or a fully rational trade-off.

2.5 Ability/prior education

It is important to correct for intelligence and, relatedly, accumulated skills and knowledge, as both are potentially correlated with time preferences and study behavior. As mentioned in the introduction, a consistent finding in the literature is that time preferences are related to measures of innate intelligence.[22] Likewise, when impatient students spend less time on their studies in secondary education, they can be expected to enter university with less skills and knowledge, which sets them behind in the course QM1. For those two reasons, it is natural to assume a negative relation between impatience and measures of ability. To the extent that measures of ability reflect accumulated skills and knowledge rather than innate intelligence, correcting for ability allows us distinguish between the contemporaneous effect of impatience and its cumulative effect. We employ two measures of ability. The first is the score on an entry test that took place the first week of the course. The test aimed to assess existing skills and knowledge and consisted of 21 multiple choice questions: 14 questions on mathematics and 7 on statistics. From the performance on this entry test, we construct two measures, one equating the number of correct answers in the mathematics part, the other one equating the number of correct answers in the statistics part. The reason for keeping the two parts separate is that they measure different things. The first measure captures mathematical ability, which can be expected to be correlated with measures of IQ. The second measures statistical knowledge, which is less suitable as a proxy for IQ, but rather reflects differences in high school education.[23]

The second measure of ability is a dummy which takes value 1 if an individual followed an advanced mathematics track in high school.[24] Apart from prior education, this variable may also proxy for intelligence, as more intelligent individuals are more likely to choose a mathematics major in high school.

[22] The distinction between innate intelligence and accumulated skills and knowledge is not clear-cut, as measures of intelligence such as standard IQ tests may also reflect cumulated skills and knowledge. However, they arguably do so to a lesser extent than, say, SAT tests (Dohmen et al. 2010).

[23] This is apparent from the fact that the score on the statistics part is hardly related to our performance measures, while it is negatively correlated with time spent in MyLab (r=–0.18). As Table 1 shows, the score on the mathematics part is strongly positively related to performance measures.

[24] A mathematical level is classified as advanced when it is the highest or one of the highest mathematical high-school levels offered in the country, i.e. 'wiskunde-b' in case of the Netherlands, 'Leistungskurs' in case of Germany, 'international baccalaureate math higher level' in case a student followed an international baccalaureate program, or self-identified by students as a high school math track in all other cases.

2.6 Control variables

In our analyses, we control for risk preferences, as risk preferences may be related to time preferences (Anderhub et al., 2001; Dohmen et al., 2010; Andreoni and Sprenger, 2012; and Sutter et al., 2013). Our measure of risk preferences is taken from the German Socio-Economic Panel and asks for individuals' stated willingness to take risks in general. It is measured on a 7-point scale, where 1 means highly risk averse and 7 fully prepared to take risks. Dohmen et al. (2011) and Vieider et al. (2015) show that this measure predicts actual behavior in incentivized lottery experiments, that it is correlated with risky behaviors in several domains, and stable across cultures. Therefore, despite its subjective nature, this seems an adequate measure of risk preferences in our setting.

The questionnaire we administered in week 6 asked students to give their best estimate of their expected exam grade for this course. This question was incentivized as follows. Students whose estimated grade was within 0.25 points of their actual exam grade participated in a lottery, in which two winners were randomly drawn. Both winners received a book voucher worth 20 euros. We use this information to capture dimensions of ability and effort that are not included in our measures of effort and ability.

Maastricht University attracts sizeable numbers of foreign students, partly because of its location close to the Belgian and German border, but also because of the language of instruction (English), and its distinct educational philosophy. In our analyses, we include dummies for the most prevalent nationalities to capture cultural differences and differences in educational systems.[25] Throughout, we also include dummies for the study program: Economics, Fiscal Economics, or International Business. Moreover, we collected measures for anxiety, persistence, and self-belief. Those measures are all constructed from the Student Motivation Scale (Martin, 2009).[26] Finally, for the course in quantitative methods we have information on the tutorial group each student belongs to, as well as on the identity of each group's tutor. When possible, we include an indicator variable on whether the tutor was a staff member (typically a PhD student) or a teaching assistant.

[25] We measure nationality rather than the country in which the student obtained his or her high school diploma. However, we observe that very few students obtain a diploma abroad. For instance, despite Maastricht being close to the Belgian and German border, none of the 51 Belgian students and only 1 out of 419 German students obtained a Dutch high school diploma. In fact, just two of the 169 students with a Dutch high school diploma in our sample do not have the Dutch nationality. Conversely, just 3 students with Dutch nationality obtained a German diploma.

[26] Each concept was measured by four items. Examples of these items are: "When exams and assignments are coming up, I worry a lot" (anxiety); "If an assignment is difficult, I keep working at it trying to figure it out" (persistence); "If I try hard, I believe I can do my university work well" (self-belief). See Martin (2009) for details.

2.7 Descriptive statistics

Our final sample combines two datasets: students who filled out the questionnaire (882 obs.) and students who were recorded in the electronic learning environment (887 obs.). Virtually all first-year students occur in at least one of the two datasets, and 860 students occur in both datasets.[27] We exclude 12 students for whom the e-learning environment recorded more than 30 practice hours of mathematics or statistics in at least one of the weeks, which is probably a recording error. We also eliminate 27 individuals who did not provide a valid answer (i.e. an inconsistent answer or no answer at all, see above) to our questions measuring time preferences. Finally, we exclude 2 repeat students from the sample, and 31 students who leave the School of Business and Economics before Christmas.[28] The reason for this latter requirement is that we are not interested in the relation between time preferences and deciding on an appropriate field of study, and therefore exclude students who apparently made a suboptimal study choice.[29] This leaves us with a sample of 788 observations. However, since not all students gave complete and consistent answers to all questions, the final number of observations in the analysis is limited to at most 766.

Table 1 shows the pairwise correlations between the most important variables. This provides valuable information about the quality of our measures of study effort. The first thing to note is that our measures of effort are significantly positively correlated. In particular, as noted above, time logged in to MyLab is highly related with the number of exercises generated (r=0.48), suggesting students are generally active when they are logged in. Time logged in is also strongly correlated with the percentage of topics completed (r=0.49). This is in line with the idea that solving the exercises is primarily a matter of effort, but ability also plays a role. The correlation of the percentage of topics completed with the entry test score on mathematics is sizeable (r=0.18). Participation in the summer course is also positively related to time spent in MyLab (r=0.22) and the number of exercises generated (r=0.13). The second thing to note is that our effort measures are not related to performance in the course QM1. This, however, is due to the fact that pairwise correlations do not take non-linearities and ability differences

[27] 27 students registered in MyLab did not fill out the questionnaire. Of those students, 60% quit their studies in the first period, and only 3 meet the BSA requirements. This suggests these students made a wrong study choice, and should therefore not be included in the sample, as we will argue above.

[28] For financial reasons, the majority of repeat students do not have an individual license for MyLab. Hence, only two repeat students are recorded in the electronic learning environment.

[29] There is clearly a relation between time preferences and dropping out early. Of those who drop out, 42% of students belongs to the most impatient category, compared to 25% in the estimation sample. Would these students have stayed in the sample, we would arguably have found stronger negative effects of impatience on performance.

into account.

A number of other relevant observations can be made from Table 1. First, impatience (included as a categorical variable that takes values from 0 to 3) is significantly negatively correlated with most measures of performance (ECTS and BSA being the exceptions), but not with any of the effort measures. As we will see, this largely corresponds to the findings in the regression analyses described in section 3. Second, in line with existing studies, students who perform better on the mathematics entry test are less impatient (r= –0.14). Interestingly, the grade in the course QM1 is highly predictive for grades in other courses (r=0.70) and academic performance in general. It is therefore safe to assume that the relation between impatience and actual study effort in the course QM1 carries over to other courses.

Figure A1 in the appendix shows the distribution of the answers to the time discounting question. Figure A2 shows the distribution of the math entry test scores, which is somewhat flatter than the normal distribution, but nicely symmetric. Figures A3-A9 display the distributions of the continuous dependent variables used in the analyses, while Table 2 provides information on the binary variables (result of final exam in QM1 and participation in the summer course). About 78% of the sample passes the final exam QM1, and 20% participates in the summer course.

3 Results

3.1 Study efforts

In this section, we test the hypothesis that impatient individuals actually exert less study effort. As described above, we have two closely related effort measures based on the electronic learning environment: recorded time logged in to MyLab and the number of exercises generated by MyLab. We complement these measures with the percentage of topics completed in order to get an idea about differences in understanding of the course material. Finally, we investigate participation in the online summer course.

3.1.1 Time logged in to MyLab and number of exercises generated

We use quantile regressions to estimate the relation between time logged in to MyLab and impatience. The reason is that the distribution of the dependent variable is right-skewed, as shown by Figure A3. Using quantile regression instead of OLS makes the results more robust to outliers.[30] In

[30] In all quantile regressions, we use the median as quantile of interest. Results are robust for using other quantiles. Likewise, results are similar when we use OLS or when we transform the dependent variable, specifically by taking logs or an indicator variable for spending an above median number of hours.

all analyses, we use dummy variables to estimate the effect of time preferences. We distinguish between three patience categories, based on individuals' switchpoint in the time discounting question. The base category is formed by relatively patient individuals, namely individuals who always prefer the delayed payment and individuals who switch to the delayed payment when the amount is €1100. The reason for combining the two relatively patient categories into one category is to obtain a more precise estimation of the effect of the two most impatient categories.[31] We use dummies because we do not know individuals' exact discount rate, but only the upper and/or lower bound. Moreover, the effect of individuals' discount rate on the dependent variable need not be linear.

Table 3 reports the estimation results. In the first column, we estimate our basic specification, correcting for gender, age, nationality, study program, and whether the tutor is a staff member of teaching assistant. We observe no differences between individuals with different switchpoints that are statistically significant at the 5% level. The point estimates are very small, given that the median number of hours logged in to MyLab is 55 hours, but the effects are rather imprecisely estimated. For instance, the 95% confidence interval for the most impatient category of individuals runs from -5.2 to 4.6, meaning that we can roughly rule out effect sizes of more than 10%, but that we cannot rule out the existence of small but meaningful differences. In the second column of Table 3, we control for ability by including a dummy for having obtained a mathematics major in high school and entry test scores. We use a flexible specification: we distinguish 6 categories of math entry test scores, and 7 categories of statistics entry test scores. However, controlling for ability does not affect the estimated effect of impatience on the time logged in to Mylab. It is worth noting that our ability measures are hardly related to time logged in to MyLab. Apparently, more talented students do not rest on their laurels, but rather aim for higher grades. In the third column of Table 3, we additionally control for risk attitude and personality characteristics such as anxiety, persistence, and self-belief. Again, this has no discernible effect on the estimated effect of time preferences.[32] In column 4 of Table 3, we add participation in the summer course to the regression, capturing a mixture of ability, motivation, and prior knowledge, but this does not affect the qualitative results. So, we find no statistically significant relationship between time preferences and time logged in to MyLab. Although we cannot rule the existence of meaningful

[31] As it turns out, the estimated coefficients of the two most patient categories are typically similar, and never differ significantly from each other. By combining those into one reference category, the coefficients of the other categories are more precisely estimated.

[32] One might be concerned that persistence captures self-control problems, and might therefore be strongly related to time preferences. It turns out that this is not the case, however. The pairwise correlation between both variables is virtually zero, and there is no relation controlling for ability and demographics.

differences, the point estimates are consistently close to zero.

As discussed above, a highly related measure of study effort is the number of exercises generated by MyLab. In Table 4, we report estimations using the number of exercises generated by MyLab as the measure of study effort. The results are very similar, in the sense that we do not find statistically significant differences. Also, the point estimates go in the opposite direction as expected, which means that we can rule out even small negative effects (effects smaller than -3.5% of the median). This suggests that our finding is not simply due to impatient students spending more time on other activities while being logged in.[33]

3.1.2 Score on problems solved

Next, we assess the relation between impatience and the percentage of topics completed in MyLab. As 25% of the students manage to complete all topics, we distinguish between students who complete all topics and those who fail to do so. Table 5 reports the estimated mean marginal effects of a probit model, where the dependent variable is 1 for students who complete all topics. The independent variables are the same as in Tables 3 and 4. As can be seen from column 3 in Table 5, the most impatient category of students are estimated to be 9 percentage points less likely to complete all topics than the reference category, even after correcting for ability, risk attitude, and personality. This effect is statistically significant at the 5% level. This suggests that impatient students have a lower understanding of the course material, although we do not find clear evidence that they spend fewer hours. This point is illustrated by the results reported in column 4 of Table 5. We additionally correct for effort by including participation in the summer course, the time logged in to Mylab, and the number of exercises generated. Specifically, we include a dummy for each quintile of the distribution of time logged in and number of exercises generated. We might expect that impatience is no longer relevant after inclusion of those variables. However, this is not the case: the estimated coefficients for impatience are hardly affected. Therefore, it seems that differences in understanding of the course material are not driven by differences in study effort. We obtain similar results when we replace the dependent variable with an indicator that distinguishes between students with an above and below median score. It should be noted, however, that when we constrain the analysis to individuals who obtain a below median score, there is no statistically significant relation between time preferences and the percentage of topics completed. A possible interpretation is that these students have such a lack of motivation that time

[33] We check the robustness of our results by excluding a number of outliers. Unreported regressions show that we obtain similar results when we exclude students who were logged in for more than 100 or 80 hours in total, and when we exclude students who attempted more than 1500 or 1000 exercises.

preferences play no role, as they exert only minimum effort anyway.[34]

3.1.3 Participation in summer course

Finally, we investigate how time preferences relate to participation in the online summer course. Table 6 presents the results of estimating a probit model, where the dependent variable equals 1 when a student participated in the summer course. The first two columns show estimates on the full sample. We observe no statistically significant differences between impatient students and the reference category. The estimated coefficients are essentially zero, although the standard errors around these estimates are substantial.

One might argue that the relationship is stronger for students with a weak background in mathematics. Theoretically, students weigh the costs and future benefits of participating in the summer course. One might expect that students with a better high school education in mathematics perceive both the benefits and the effort costs as lower. As individual differences in time discount rates play a larger role when future benefits are high, we might expect a stronger relation when we restrict the sample to students with a weak background in mathematics. In columns 3 and 4 of Table 6, we restrict the sample to students who were on a high school track in which mathematics was a major or a minor subject, respectively. Contrary to our expectations, we find no relation in the sample of students with a weak background in mathematics. In fact, we find more evidence for a relation among students with a major in mathematics. However, we should not overinterpret this finding, as only 34 students with a major in mathematics participate in the summer course.

3.2 Performance

In this section, we first investigate the relation between impatience and performance in the course QM1, where performance is measured by final exam grades and the probability of failing the final exam. The analysis of performance in the course QM1 is of particular interest, as we analyze the relation between impatience and study effort in the context of the course QM1. Then, we analyze other measures of academic performance in the first year in order to get the complete picture.

[34] Students with a below median score (98%) are on average 52 hours logged in during the period, while students with an above median score spend on average 66 hours in MyLab. Although some students with a below median score may simply lack the ability to obtain a high score, this suggests that a substantial number of those students also lack the motivation to complete almost all topics.

3.2.1 Performance in the final exam in QM1

Table 7 reports the results of a Tobit estimation of individuals' final exam grade in QM1 as a function of their discount rates. As a significant fraction of students obtain the highest possible grade (see figure A6 in the appendix), we use a Tobit model to account for the right-censoring of the data.[35] The first column of Table 7 shows that the most impatient category of individuals obtains a significantly lower grade than the reference category, correcting for gender, age, nationality, study program, and whether the tutor is a staff member or teaching assistant. The effect is not only statistically significant, but also meaningful in economic terms: the difference is about 1.1 points on a 10-point scale. The difference between the reference category and the category of individuals who switches when the delayed payment is €1250 is much smaller, and statistically significant only at the 10% level. This effect becomes insignificant once we add controls.

In the second column of Table 2, we control for students' ability by adding dummies for their score on the entry tests, as well as a dummy for having obtained a mathematics major in high school. Those measures reflect innate intelligence as well as accumulated skills and knowledge, and are therefore likely to be endogenous with respect to time preferences. This is important for the interpretation of the results: the estimates reported above can be seen as an upper bound of the cumulative effect of time preferences on performance.[36] Correcting for ability gives us the contemporaneous effect. In line with existing studies (Cadena and Keys, 2015; De Paola and Gioa, 2013; Golsteyn et al., 2014), the estimated coefficient decreases in absolute magnitude when controlling for ability as revealed at the start of the academic year, but remains sizeable and statistically significant. The effect size is about one quarter of a standard deviation. Next, we add controls for risk attitude and measures of personality. This, however, has only a minor impact on the estimated effect of time preferences.

The key question is whether differences in impatient students' grades can be attributed to differences in study effort. We have already seen that there is no relation between time preferences and time logged in to MyLab, the number of exercises generated by MyLab, and participation in the summer course. Column 4 of Table 7 reports estimations controlling for those variables. Specifically, we include a dummy for each quintile of the distribution of time spent and number of exercises generated.[37] The estimation results confirm that differences in performance are not driven by differences in effort as measured by activity in MyLab and participation in the summer

[35] We obtain similar results when we use OLS. Five students did not show up for the first exam QM1, and are treated as missing.

[36] It is an upper bound, because we do not know to what extent our ability measures reflect prior investments or innate intelligence.

[37] The results are very similar when we estimate models that allow for interactions between our measures of effort and entry test scores. Results are available upon request.

course. In column 5, we additionally control for the percentage of topics completed. We use a non-linear specification by including dummies for 5 categories.[38] Their inclusion clearly reduces the negative effect of impatience on performance, but the estimated coefficient for the most impatient category remains sizeable and statistically significant at the 5% level. In column 6, we further control for effort and ability by including individuals' grade expectations. Again, this leads to a drop in the estimated effect of impatience, and the effect is only statistically significant at the 10% level. So, by extensively controlling for effort and ability, we can largely explain the negative effect of impatience on the final exam grade in QM1. However, the differences in performance cannot simply be explained by differences in activity in MyLab or understanding of the course material as revealed by the fraction of topics completed.

Arguably, the relation between patience and grades is stronger than the relation between patience and passing or failing the exam, as the benefits of obtaining a higher grade materialize in the remote future, while failing the exam has more immediate consequences. Table 8 presents the results of estimating a probit model, where the dependent variable takes the value 1 if a student failed the final exam in QM1, and 0 otherwise. Coefficients report mean marginal effects. Column 1 shows that individuals who always prefer the immediate payment have a 13.4 percentage point higher estimated probability of failing the exam than the reference category, correcting for the usual demographics. This effect is substantial, as only 22% of our sample fails the first exam in QM1. The point estimates become smaller and statistically insignificant when we add controls for ability, risk attitude, and other personality characteristics (columns 2-3). The estimated effect of impatience is essentially zero when correcting for study effort (columns 4 and 5) and expected exam grade (column 6). So, although impatient students obtain a lower grade for the final exam in QM1, we find no evidence for a contemporaneous effect of impatience on the probability of passing the exam.

3.2.2 Performance in other courses

An important question is to what extent the relation between patience and study results in the course QM1 is representative of other courses. To answer this question, we examine the relation between patience and academic performance in other first-year courses than QM1. Our first measure of performance is the GPA, i.e. the ECTS-weighted average of the final exam grades obtained in all first year courses except QM1. We only consider final exam grades obtained in the first attempt and exclude results obtained in

[38] The five categories do not perfectly correspond to the quintiles of the distribution, as 25% of the sample obtains the highest possible score.

the resit.[39] We estimate the model using OLS, since the distribution of the GPA is not censored, as shown by figure A7 in the appendix.

Table 9 shows the results of regressing the GPA on time preferences and the same set of controls as before (except for whether tutors are staff members of teaching assistants). The first thing to note is that, regardless of the exact specification, the most impatient category of individuals obtains significantly lower grades than individuals who are more patient. In fact, the relation between patience and the GPA is virtually the same as the relation between patience and the grade obtained in the course QM1. The estimated effect sizes are similar after standardizing: correcting for ability, risk attitude, and personality, the expected grade of the most impatient students is about one quarter of a standard deviation lower than the expected grade of the reference category. In this sense, the relation between patience and grades we observe in the context of QM1 seems highly representative of other first year courses.

The second thing to note is that although our measures of ability and effort are obtained in the specific context of QM1, they are strongly related to the average grade obtained in other courses. The measures of ability jointly add substantial explanatory power, as shown by the difference in R^2 between columns 1 and 2. When adding the full set of controls for effort and ability (column 6), we explain almost half of the variation in exam grades. Nevertheless, the relation between impatience and grades remains marginally significant after controlling for ability and effort.

Next, we assess whether impatient students' lower GPA also translates into a higher probability of failing an exam. Specifically, we count the number of courses (other than QM1) in which a student failed the final exam, conditional on participating in that exam. Not participating in a course's final exam is not considered as a failed exam, since we do not know the grade the student would have obtained if he had participated.[40] We estimate a negative binomial count model that corrects for exposure to the number of final exams taken. The estimation results, presented in the first two columns of Table 10, are comparable to the results on GPA: students who belong to the most impatient category fail more final exams. The effect is sizeable: the most impatient category fails 44% more exams than the reference category. This effect partially reflects impatient students' lower ability at the start

[39] Results are similar when we investigate average final grades, i.e. including the resit results in the average. This is unsurprising, given that the correlation between the average grade based on first sit and final grades is 0.98.

[40] Clearly, students who do not show up at the exam may do so for a specific reason. For instance, students may stay at home because they expect to fail anyway, or because their strategy is to take the resit exam later in the year, as the additional time allows for a better preparation. We therefore checked whether participation in a course's final exam is related to impatience, and do not find a statistically significant relation between the two. We also redid our analysis assuming that students who did not participate, failed the exam. This does not affect the qualitative results.

of the academic year. To the extent that our ability measures reflect lower prior investments (rather than innate ability), this effect can be viewed as the cumulative effect of impatience. When we include our controls for ability, impatient students are estimated to fail about 31% more exams than the reference category, which amounts to almost 0.5 additional failed exam per academic year. Thus, the most impatient individuals do not only obtain lower grades in the final exams, they are also more likely to fail these exams. The course QM1 seems to be the exception in this respect, arguably because the stakes are higher than for other courses, since the BSA criteria require passing at least one of the courses in quantitative methods.[41]

An important question from the perspective of social welfare is whether impatient students earn fewer ECTS in the first year. This is not implied by lower performance in the final exams: impatient students may perform relatively well in the re-examinations, and consequently earn a similar number of ECTS as less impatient students. As the distribution of ECTS is naturally bounded between 0 and 60 ECTS, with the majority (55%) of students obtaining the highest possible number of ECTS and a negligible (1%) number obtaining zero ECTS, we first estimate a probit model where the dependent variable equals 1 when a student passes all courses, and 0 otherwise. The results are reported in columns 3 and 4 of Table 10. The most impatient category of students has a 12 percentage point smaller chance of passing all first year courses than the reference category (column 3). This is a substantial effect, given that 55% of the sample obtains 60 ECTS. When we control for ability, risk attitude, and personality, the estimated coefficient reduces to 6 percentage points, as can be seen in column 4 of Table 10. The coefficient is also no longer statistically significant (p=0.21), but it should be noted that the standard errors are too large to detect even substantial effect sizes (below 10 percentage points). The effect seems restricted to the extensive margin (i.e. obtaining all ECTS or not). When we estimate an OLS regression on the sample of students who do not obtain all ECTS, we do not find any relation between impatience and the number of ECTS obtained, as shown in column 5 of Table 10. The point estimates are close to zero and go in the opposite direction as we would expect. Unreported regressions show that this result continues to hold when we do not control for ability, when we exclude students with particularly bad performance in terms of the number of ECTS obtained (using various thresholds), and when we exclude students

[41] Consistent with this argument, we observe a similar pattern in the course QM2: impatient students obtain lower grades, but do not fail more often. We analyze this in more detail by exploiting the fact that when taking the course QM2, some of the students have passed the course QM1, while others failed and consequently have to pass QM2 to meet the BSA criteria. Thus, if the stakes are key, we would expect that impatience has a negative effect on the probability of passing the exam in QM2 for students who already passed QM1, but not for those who failed QM1. We don't find this pattern. The evidence is therefore inconclusive.

who fail to meet the BSA requirements. Also, we do not find a statistically significant relationship when we combine intensive and extensive margin by estimating a count model.[42] So, although the most impatient category of students unambiguously shows worse performance in final exams than more patient students, this is not clearly reflected in a lower number of ECTS.

In columns 6 and 7 of Table 10, we analyze the relation between receiving a negative BSA and impatience. We estimate a probit model where the dependent variable equals 1 if a student received a negative BSA, and 0 otherwise. We find no indication that impatient students are more likely to receive a negative BSA than more patient students. In fact, the estimated coefficients of the impatience dummies are small relative to the percentage of students who receive a negative BSA (13% of the sample), and typically go in the opposite direction from that predicted by theory. So, although highly impatient individuals show generally weaker academic performance, this remains without severe negative consequences by the end of the first year. This result is particularly remarkable in the light of the fact that impatient students demonstrate lower skills and knowledge when they enter university.

These findings suggest that impatient students tend to shift their study efforts to the resit exams. Although impatient students do not exert less effort for the first exam, their relatively weak performance suggests that they should have exerted more effort to obtain the same grade or to pass the course. As they are more likely to pass in the resit, they apparently do so when preparing for the resit exam.[43] This behavior is perfectly consistent with their time preferences, for two reasons. First, it is optimal to postpone the study effort required to pass the course, as expected future study efforts are more heavily discounted. Second, impatient students may perceive study delay as more problematic, which increases their incentives to pass the resit exam. Interestingly, this result also suggests that impatient individuals in our sample do not suffer from *severe* self-control problems. If they had severe self-control problems, we might expect that impatient students also obtain fewer ECTS and receive a negative BSA more often. This is not the case, however. Note that this does not imply that impatient individuals make fully rational trade-offs: all we can say is that their possible self-control problems are limited to the first exams, and that they are apparently able to overcome self-control problems when the consequences of underperforming become more severe.[44]

[42] We also find no differences between high and low ability students, as measured by their math entry test score. More generally, we will analyze the interaction between impatience and ability in more detail in subsection 3.3.

[43] In line with this interpretation, we find that impatient individuals are more likely to pass, but do not generally obtain higher grades in resit exams.

[44] Of course, we cannot rule out that impatient students are more likely to drop out after the first year, but dropout rates among students who survived the first year are relatively low. For instance, of the cohorts of students who started a Business study at Maastricht

3.3 Estimation by ability

In this section, we analyze how the relation between time preferences, academic performance, and study effort depends on ability. From a theoretical perspective, there is an ambiguous relation between ability and the effect of impatience on study behavior. On the one hand, one could argue that impatience is less relevant for students of low ability, because they exert maximum effort anyway. On the other hand, one could argue that impatience is less relevant for students of high ability. Since high ability students may perceive the marginal benefits of effort as low (they are sure to pass the exam anyway), a change in impatience has little effect.[45] One could also argue that the future marginal benefits of effort are much larger for high ability students, and that a change in valuation of the future therefore has a large effect. So, from a theoretical perspective, the relation between time preferences, academic performance, and study effort may be different for students of different ability. To examine this, we split the sample in a low, medium, and high ability group, based on the scores on the mathematics entry test. Students with a score above 8 are classified as high ability students, while students with a score below 6 are classified as low ability students. Those with a score between 6 and 8 are classified as medium ability students.

Table 11 reports the results of re-estimating the relations between impatience, study results, and study effort by ability. In all regressions we include, in addition to the standard control variables, controls for ability, risk attitude, and personality. The key finding is that the effects of impatience seem concentrated among relatively able students, but the overall pattern is not different than that observed for the sample as a whole. Also, the estimated effects of impatience on performance seem consistently smaller in absolute value for students of medium ability. The effects are also statistically insignificant, but this may be due to the reduced sample size. A final

University in 2005, 22% dropped out in the first year (107 students). Of the remaining students, only 4% dropped out in subsequent years (15 students).

[45] Suppose students choose effort to maximize the following utility function:

$$u = \delta f(e, a) - c(e),$$

where $f(e, a)$ and $c(e)$ denote, respectively, the future benefits and present costs of study effort e, while a denotes ability and δ captures patience. Assuming the problem is concave, i.e. $f_e > 0$, $f_{ee} \leq 0$, $c_e > 0$, and $c_{ee} > 0$, it is easily verified that the optimal effort level is increasing in patience δ:

$$\frac{de}{d\delta} = \frac{f_e}{c_{ee} - \delta f_{ee}} > 0$$

The impact of a change in δ on optimal effort depends on the magnitude of the terms f_e and $c_{ee} - \delta f_{ee}$. When ability is low, c_{ee} goes to infinity when effort approaches a natural maximum, hence $\frac{de}{d\delta}$ is small. When ability is high, f_e may be close to zero, hence $\frac{de}{d\delta}$ may be close to zero. Alternatively, when ability and effort are complements, f_e may be relatively high for able students.

point worth noting is that the effect of impatience on effort is not generally negative, and nowhere close to significant. So, the evidence suggests that the relation between time preferences and academic performance is concentrated among relatively able students, and seems rather weak for mediocre students.

4 Discussion

The overall picture that arises from our analyses is that impatient individuals show weaker performance. Impatient students obtain lower grades and fail a final exam more often, suggesting that they put in less effort into their studies. However, we find no evidence that impatient students actually study fewer hours or practice fewer exercises. We also do not find clear differences in summer course participation. The question is how to reconcile these findings. If impatient students do not study fewer hours, why do they obtain lower grades?

Below we discuss a number of possible explanations that fall into three different categories. The first explanation is that impatient students have a less efficient learning style. That is, they do something different that explains why they perform worse while investing just as much time in their studies. For example, they may work less concentrated than patient students. The second explanation is that our measures of effort ignore important other dimensions of effort that explain impatient students' weaker performance. For instance, impatient students might be less inclined to attend lectures and study written course materials. The third explanation is that impatient students are of lower unobserved ability: they exert just as much effort as patient students and do not differ in their learning style, but because of their lower ability they should have exerted more effort to obtain the same grade.

It is important to note that those explanations have different implications for the question whether impatient students actually exert less effort. When performance differences can be attributed to differences in learning styles or unobserved ability (first and third explanation), the conclusion should be that there is no evidence that impatient students exert less effort. By contrast, when our measures of effort ignore relevant dimensions of effort (and are not positively correlated with those dimensions), the performance differences indicate that there are in fact effort differences, and the evidence is consistent with the theoretical prediction. We will now discuss each of those explanations in more detail.

4.1 Differences in learning style

First, consider the explanation that impatient individuals study less efficiently because they have a different learning style. The analysis proceeds as follows. We start out by investigating whether there are differences in the amount of time impatient students spend on each exercise in MyLab. Next, we analyze differences in the use of the electronic assistance tools "Help me solve this" and "View an example". Then, we investigate differences in the allocation of study effort over the course period. Finally, we briefly touch on survey evidence on differences in learning styles.

We have already seen that there are no differences in the amount of time spent in MyLab as well as the number of exercises generated by MyLab. The first step in our analysis of learning styles is to combine these two measure to estimate the effect of impatience on the amount of time spent on each exercise. The quantile regression results are reported in the first column of Table 12. We find that, perhaps somewhat surprisingly, the category of most impatient students spend less time per exercise. This rules out that impatient students spend more time on other activities (such as communicating via Facebook or WhatsApp) when they are logged in, since if that was the case we would expect them to spend more time on each exercise. Rather, the results suggest that impatient students study the exercises more superficially, which might explain why impatient students show weaker performance despite similar levels of activity in MyLab. However, controlling for time spent per exercise hardly affects the relation between impatience and the fraction of topics completed or final exam grades. This is illustrated in the second column of Table 12 for the fraction of topics completed. Moreover, the finding that impatient students spend less time per exercise can only explain their relatively weak performance if time spent per exercise is positively related to performance. We find no evidence that this is the case, however.[46] A further reason why it is unlikely that differences in time spent per exercise explain our results is that the estimated effect is not very robust[47] and the effect size is not huge (8% less time per exercise as compared to the most patient group).

To shed further light on differences in activities in MyLab, we analyzed the use of the electronic assistance tools "Help me solve this" and "View an example". The distributions of these variables are shown in figures A10 and A11. First, we assess whether there are absolute differences in the use impatient individuals make of the electronic asistance tools. We estimate quantile regressions. As can be seen in columns 3 and 4 of Table 12, there is no statistically significant relationship.[48] This underlines our previous finding that there are no differences in MyLab activity. Next, we investigate

[46] In the regression we control for time logged in and number of exercises generated. We also do not find a positive effect of time per exercise when we drop those controls.

[47] For instance, the effect becomes insignificant once we use the 0.33 or 0.75 quantile in the quantile regression rather than the median. Likewise, estimated effect sizes are typically much smaller and statistically insignificant when we use ols in combination with different cut-off rules to account for outliers.

[48] We assess the robustness of the estimates for outliers. We also assess the robustness for censoring at zero (19 and 34 observations in case of guided solutions and sample problems, respectively) by estimating a tobit specification. This does not affect the results.

whether there are differences in the tendency to use the electronic assistance tools relative to the number of exercises generated by MyLab. The results are reported in columns 5 and 6 of Table 12. We find no indication that impatient students use the electronic assistance tools at a higher or lower rate per exercise. In the light of those results, it is not surprising that differences in the use of electronic assistance tools cannot explain impatient students' weaker performance.[49]

Another possibility is that impatient students spend their time less effectively, because they allocate their study efforts differently over the course period. Intuitively, one might expect that impatient individuals will be more inclined to procrastinate, i.e. postpone their study efforts to the end of the course period. Unfortunately, the MyLab data do not allow us to observe when precisely students were active. However, problems (topics) are structured by weekly problem sets, and MyLab records information on time logged in, number of exercises generated, and fraction of topics completed by problem set. Assuming that students work on the problem sets in the scheduled order, we might expect that procrastination leads to a relatively low effort on the topics discussed in the final weeks of the course. Students who procrastinate will be under higher time pressure when the exam is coming up, and may therefore decide to spend less time on the final week's problem set to free up time for more urgent study activities. We test this in two ways. First, we estimate the relation between impatience and study effort for each of the weekly problem sets. The results are reported in Table 13. It is noteworthy that we find a clear negative effect of impatience on time spent on the final homework set (week 7), but this is not reflected in a lower number of exercises generated or a lower probability of completing all topics in the final homework set. Generally speaking, the association between impatience and measures of study effort does not become stronger towards the end of the course period. For the second analysis to detect time patterns we create a panel by pooling the weekly data. We then estimate a panel regression with individual and time fixed effects, interacted with time preferences, math entry test scores, and high school math education. By doing so, we correct for all time-invariant unobservable characteristics that affect the level of effort (but not for characteristics that affect the changes in effort over the course period). The results are reported in Table 14. They paint a very clear picture: the most impatient category of individuals give less attention to the final homework set as compared to others. In an attempt to reconcile this finding with the lack of a time pattern in Table 13, we checked whether this divergence in findings can be attributed to the different set of control variables. We find no evidence that this is the

[49] When we include the requests for guided solutions ("Help me solve this") and sample problems ("View an example") as controls in the analysis of exam grades or fraction of topics completed, the estimated coefficient of impatience is hardly affected.

case. Importantly, we investigate whether time logged in to MyLab in week 7 and number of exercises generated in week 7 explain impatient students weaker performance when we include them as additional control variables in our analyses of performance differences. Their inclusion does not affect the estimated effect of impatience in any meaningful way. So, although the data supports the idea that impatient students allocate their study efforts differently over the course period, it does not seem to be a good explanation for their relatively weak performance. Another reason why procrastination is not a good explanation is that this specific setting is not very conducive to such behavior. In the course QM1, the midterm exams provide strong incentives to study the course material regularly.

Finally, we collected survey information on students' learning styles. We distinguish between six different learning styles using the learning style model of Vermunt and Vermetten (2004). We do not find any relation between time preferences and self-reported learning styles, and consequently none of our results is affected by the inclusion of learning styles in the regressions.

4.2 Unobserved effort dimensions

An alternative explanation for our findings is that by concentrating on time spent in an electronic learning environment, we ignore important other dimensions of study effort that explain impatient students' weaker performance. Since MyLab offers direct feedback and immediate rewards via text messages ("Correct!, Good!, Congratulations!, Fantastic!, Excellent!"), impatient students may have a relatively strong preference for using MyLab over studying written course materials, implying that we do not find differences in measured study effort, despite differences in total study effort.[50] Obviously, we do not have precise information on the effort exerted outside the electronic learning environment, but we have a number of indications that render this explanation implausible. First, effort in the electronic learning environment is related to grades in the regressions, suggesting that our measures accurately reflect total effort. For example, differences in time spent in MyLab explain substantial differences in the grade QM1 by na-

[50] A related explanation for our findings is that impatient students prepare just as well for the exam as patient students, but they put in less effort to obtain a good result during the exam. This explanation would be in line with Borghans et al. (2008), who find that non-cognitive skills, including time preferences, influence performance on cognitive tests, even when those test are incentivized (see Segal, 2012, for a similar result). However, it seems inconsistent to assume that impatient students have no difficulties with studying as intensively as patient students, while at the same time assuming that they are not able to put in similar effort during the exam, when the marginal to returns to effort are so much higher than when practicing. Moreover, impatient students are less likely to complete all topics in MyLab, suggesting that they are less well prepared. We therefore do not think this is a plausible explanation.

tionality.[51] Second, we capture study efforts outside the electronic learning environment by participation in the summer course, which is not related to time preferences. Finally, we find no differences when we use the total number of study hours students report in our questionnaire. As self-reported data may be hampered by measurement error we should be careful not to overinterpret this result, but this finding is nevertheless suggestive.

4.3 Differences in unobserved ability

The most plausible explanation is that impatient students are of lower unobserved ability: they exert just as much effort as patient students, but should have exerted more effort to obtain the same grade. As noted in the introduction, previous studies have found that impatience is associated with lower scores on intelligence tests (Frederick, 2005, Shamosh and Gray, 2008, Dohmen et al., 2010). Assuming that unobserved ability is positively related to observed ability, the fact that impatience and ability, as measured by the score on the mathematics entry test, are negatively correlated (r=–0.14) is in line with this explanation. Furthermore, it is suggestive that we find no relation between impatience and time spent in MyLab, whereas we find a negative relation between impatience and the percentage of topics completed. These two measures are highly correlated (r=0.49), but an important difference between the two is that the former is somewhat negatively related to the score on the math entry test (r=–0.09), while the latter is clearly positively correlated (r=0.18). Although these findings do not provide conclusive evidence that time preferences capture unmeasured ability, they are at least consistent with such an interpretation.[52]

5 Concluding remarks

We analyze the relation between time preferences, study effort, and academic performance among first-year business and economics students. We test the hypothesis that impatient students exert less effort, and consequently show weaker academic performance. The main contribution of our study is that we relate time preferences to direct measures of study effort. We collect information on study efforts of 766 students for an obligatory course in quantitative methods. In particular, we exploit data from an electronic learning

[51] As it turns out, students with German nationality do much better than other nationalities. Correcting for ability and personality, they earn on average 0.55 point higher exam grade in QM1. Correcting for time spent in MyLab, this difference becomes 0.33 and statistically insignificant (p=0.18).

[52] It need not be intelligence per se, but can also be social background, which has been related to academic performance as well as time preferences (see Björklund and Salvanes, 2011, for a review on the effect of social background on educational attainment, and Delaney and Doyle, 2012, for evidence on the link between time preferences and social background). Social background can be interpreted as unobserved ability.

environment that records the time students are logged in, the number of exercises generated by the system and whether students manage to solve at least one exercise associated with a particular topic. Also, we have information on whether students participate in an online summer course. Time preferences are measured by stated preferences for an immediate payment over larger delayed payments.

Our main finding is that there is no statistically significant relationship between student's time preferences and the effort they actually put into their studies. We find no statistically significant relationship between time preferences and the time students are logged in, the number of exercises generated, and participation in the summer course. All estimated effects are close to zero, though often estimated with a substantial margin of error. However, we find evidence that impatient students are less likely to complete all topics. This suggests that impatient students have a lower understanding of the course material, but this cannot be attributed to lower effort in the sense of lower time investments or a lower number of exercises generated.

In line with this finding and previous studies (Kirby et al., 2005, Cadena and Keys, 2015, De Paola and Gioia, 2013, Golsteyn et al., 2014), we find a negative relation between impatience and the grade obtained in the final exam in quantitative methods, as well as exam grades obtained in other first-year courses. Moreover, impatient students fail final exams more often (excluding resit results). This effect is statistically significant and sizeable: students who always prefer the immediate payment are estimated to fail 31% more exams than other students who demonstrate a similar ability level at the start of the academic year. This amounts to 0,5 additional failed exam per year. The effect of impatience is even larger when we acknowledge that time preferences may also affect performance via lower prior investments in skills and knowledge: an estimated upper bound of this cumulative effect is 44%. However, since our estimates suggest that impatient students do not exert less effort, their weaker performance cannot simply be attributed to lower effort.

The most plausible explanation for this result is that impatient students are of lower unmeasured ability. Consistent with this interpretation and in line with existing studies (Frederick, 2005, Shamosh and Gray, 2008, and Dohmen et al., 2010), we find that impatience is negatively correlated with measures of ability. Consequently, to the extent that ability is unobserved or measured with error, the estimated negative impact of impatience on educational performance is larger than can be explained by differences in effort. As an alternative explanation, we also find some indication that impatient students have a less efficient learning style. They seem to spend less time per exercise and to invest less time studying the final weeks' homework set. The latter finding suggests that they have a more tight time constraint at the end of the course period when the exam date is approaching, which suggests they procrastinate studying. However, time per exercise and study effort on the final homework set cannot account for the negative effect of impatience on performance. Regardless which of those interpretations is true, they both imply that impatient students' lower performance cannot be fully attributed to lower study investments. It should be noted, however, that our results are not necessarily inconsistent with the theoretical prediction. Relative to their true ability, impatient students should have exerted more effort to obtain the same grade. In this sense, they exert little effort.

An important second finding is that impatient students in our context do not seem to suffer from *severe* self-control problems. Correcting for ability differences at the start of the acamic year, impatient students are not significantly less likely to earn all study credits that can be earned during the first year. Moreover, they are not less likely to meet the university's minimal requirements for first year's performance, even when we ignore initial ability differences. This suggests that impatient students in our sample do not suffer from *severe* self-control problems. They may certainly act impulsively, although we find no clear evidence for this, but they apparently manage to avoid strong adverse consequences of impulsive behavior. In fact, their higher probability of passing in the resit is consistent with their time preferences, as they may prefer postponing study effort, and consider study delay as more costly.

When interpreting these results, we should keep in mind that they are derived in a specific setting. Students face strong incentives to study regularly, as in most courses they have the opportunity to take at least one midterm test and they are required to attend weekly tutorials, where active participation is expected. In this sense, this is a strong test of the hypothesis that impatient students put less effort into their studies. Also, our finding that impatient students do not suffer from severe self-control problems should be seen in the context of our sample of university students, who are arguably less naive than the general population (see De Paola and Gioia, 2013, for similar findings in a similar context). Nevertheless, the fact that we find substantial effects of impatience on grades and final exam results, despite insignificant differences in study activity, calls into question whether impatient individuals' weak performance is actually driven by low study effort, or reflects a lower unobserved ability or perhaps an inefficient learning style. Previous literature may sometimes have too easily inferred differences in effort from differences in performance. This underlines the value of taking a different perspective by using direct measures of study effort.

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Tables

Table 1: Correlation table

	Impatience	Time in MyLab	Number of exer-cises gen-	Summer course	Fraction of topics com-pleted	Score entry test math	Score entry test statistics	Math major	Grade first sit exam QM1	Failed first sit exam QM1	GPA all courses excl. QM1	Number of failed first sit exams	ECTS	Received binding study advice
Impatience	1.00													
Time in MyLab	0.03	1.00												
Number of exercises	0.06**	0.48***	1.00											
Summer course	-0.03	0.22***	0.13***	1.00										
Fraction of topics completed	-0.05	0.49***	0.57***	0.15***	1.00									
Score entry test math	-0.14***	-0.09**	-0.06	0.05	0.18***	1.00								
Score entry test statistics	-0.09*	-0.18***	-0.14***	-0.10***	-0.06	0.11***	1.00							
Math major	-0.08**	-0.11***	-0.14***	-0.13***	0.02	0.33***	-0.04	1.00						
Grade first sit exam QM1	-0.16***	0.01	0.03	0.04	0.47***	0.41***	0.09**	0.25***	1.00					
Failed first sit exam QM1	0.11***	-0.01	-0.02	-0.04	-0.37***	-0.33***	-0.04	0.22***	-0.78***	1.00				
GPA all courses	-0.15***	0.09***	0.06	0.09***	0.40***	0.25***	0.06*	0.09**	0.70***	-0.47***	1.00			
Number of failed first sit exams	0.14***	-0.04	-0.01	-0.07**	-0.31***	-0.19***	-0.10***	-0.09**	-0.60***	0.43***	-0.84***	1.00		
ECTS	-0.05	0.16***	0.17***	0.07*	0.50***	0.20***	0.02	0.10	0.65***	-0.56***	0.76***	-0.66***	1.00	
Received binding study advice	0.02	-0.15***	-0.19***	-0.03	-0.43***	-0.15***	-0.02	-0.11	-0.48***	0.44***	-0.56***	0.45***	-0.84***	1.00

Note: stars indicate significance as follows: ***p<0.01, **p<0.05,*p<0.1. GPA and number of failed first sit exams exclude results obtained in the course QM1. Impatience is a categorical variable taking values 0-3

Table 2: Descriptive statistics

	Mean	Std dev.	Median	Min	Max
Effort related variables:					
Time logged in to MyLab (total hours)	59.0	25.6	55.4	1.1	164.6
Number of exercises generated by MyLab	468.6	197.7	454.5	0	2178
Participated in summer course (yes=1, no=0)	0.20	0.40	0	0	1
Fraction of topics completed	0.88	0.21	0.98	0.01	1
Completed all topics (yes=1, no=0)	0.25	0.43	0	0	1
Performance related variables					
Grade final exam in QM1	7.2	2.2	7.5	1.5	10
Failed final exam in QM1 (fail=1, pass=0)	0.22	0.42	0	0	1
GPA all courses except QM1	6.6	1.3	6.7	1.9	9.5
Number of failed exams (excluding QM1)	1.6	1.9	1	0	8
ECTS	50	15	60	0	60
Obtained all ECTS (yes=1, no=0)	0.55	0.50	1	0	1
Received a negative bsa (yes=1, no=0)	0.13	0.34	0	0	1
Learning style related variables					
Time logged in per exercise	0.14	0.13	0.12	0.04	2.31
Guided solutions	73.6	95.6	41	0	1049
Sample problems	186.1	111	184	0	598
Guided solutions per exercise	0.15	0.16	0.10	0	2.50
Sample problems per exercise	0.43	0.30	0.40	0	3.36

N=766 except for exam results in QM1 (N=761), guided solutions and sample problems (N=737), time logged in per exercise, guided solutions per exercise, and sample problems per exercise (N=735).

Table 3: Study efforts: time logged in to MyLab

Method: Quantile Regression	**Total hours logged in to MyLab**			
	(1)	(2)	(3)	(4)
Always delayed or switch when delayed is €1100		*Reference*		
Switch when delayed is €1250	3.74*	2.44	3.45*	2.55
	(2.25)	(1.93)	(1.85)	(1.79)
Always Immediate	-0.30	-0.52	-1.02	-1.46
	(2.49)	(2.28)	(2.36)	(2.35)
Mathematics major		-1.11	-3.49**	-1.35
		(2.05)	(1.77)	(1.77)
Score on math entry test= 0 to 3			*Reference*	
Score on math entry test= 4 to 5		0.68	-1.80	-2.39
		(4.12)	(4.14)	(3.40)
Score on math entry test= 6 to 7		-5.06	-5.00	-8.44***
		(3.28)	(3.85)	(3.13)
Score on math entry test= 8 to 9		-3.16	-2.16	-5.65*
		(3.53)	(3.93)	(3.40)
Score on math entry test= 10 to 11		-4.06	-4.87	-7.69**
		(3.84)	(4.25)	(3.44)
Score on math entry test= 12 to 14		-5.93	-4.01	-7.73*
		(4.89)	(4.69)	(4.14)
Score on statistics entry test= 0			*Reference*	
Score on statistics entry test= 1		-3.20	-5.26*	-6.22*
		(3.36)	(3.05)	(3.18)
Score on statistics entry test=2		-4.75	-9.11***	-9.81***
		(2.96)	(2.84)	(3.10)
Score on statistics entry test= 3		-4.64*	-5.25*	-6.48**
		(2.77)	(2.74)	(3.02)
Score on statistics entry test=4		-8.67***	-12.93***	-14.11***
		(2.72)	(2.76)	(2.75)
Score on statistics entry test= 5		-3.33	-4.80	-5.99
		(3.49)	(2.99)	(3.71)
Score on statistics entry test= 6 to 7		7.56	2.10	3.43
		(11.22)	(3.93)	(5.60)
Summer course				7.39***
				(2.42)
Demographics	yes	yes	yes	yes
Personality	no	no	yes	yes
Observations	766	766	766	766
Pseudo r2	0.09	0.11	0.14	0.14

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. The quantile used in the regression is the median.
Control variables:
Demographics: gender, age nationality, study program, and whether the tutor is staff member or teaching assistant.
Personality: risk attitude, anxiety, persistence, self-belief.

Table 4: Study efforts: number of exercises generated by MyLab

Method: Quantile Regression	Number of exercises generated by MyLab			
	(1)	(2)	(3)	(4)
Always delayed or switch when delayed is €1100		*Reference*		
Switch when delayed is €1250	3.31	-8.06	-4.69	-1.67
	(10.92)	(11.31)	(11.24)	(11.21)
Always Immediate	28.53*	20.81	13.98	13.17
	(14.74)	(16.37)	(15.60)	(16.26)
Mathematics major		-28.28**	-26.19**	-28.97**
		(11.50)	(11.47)	(11.46)
Score on math entry test= 0 to 3			*Reference*	
Score on math entry test= 4 to 5		-26.93	-32.82	-38.29*
		(23.54)	(21.72)	(22.11)
Score on math entry test= 6 to 7		-4.68	-3.65	-10.23
		(23.23)	(23.82)	(23.36)
Score on math entry test= 8 to 9		-20.50	-22.59	-23.01
		(23.30)	(22.44)	(22.86)
Score on math entry test= 10 to 11		-19.79	-17.92	-24.73
		(23.85)	(23.78)	(24.37)
Score on math entry test= 12 to 14		-42.00	-37.28	-34.91
		(27.66)	(28.97)	(27.87)
Score on statistics entry test= 0			*Reference*	
Score on statistics entry test= 1		-5.28	11.33	6.59
		(20.36)	(20.33)	(19.78)
Score on statistics entry test=2		-16.80	-11.02	-12.85
		(18.43)	(19.97)	(19.36)
Score on statistics entry test= 3		-36.07*	-25.38	-25.38
		(18.50)	(19.26)	(18.99)
Score on statistics entry test=4		-42.49*	-38.49*	-34.09
		(23.94)	(22.95)	(23.31)
Score on statistics entry test= 5		-26.35	-30.66	-32.25
		(22.40)	(27.79)	(27.70)
Score on statistics entry test= 6 to 7		-5.41	2.78	-0.44
		(27.61)	(26.88)	(37.58)
Summer course				8.61
				(13.81)
Demographics	yes	yes	yes	yes
Personality	no	no	yes	yes
Observations	766	766	766	766
Pseudo r2	0.09	0.11	0.14	0.14

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. The quantile used in the regression is the median.
Control variables:
Demographics: gender, age nationality, study program, and whether the tutor is staff member or teaching assistant.
Personality: risk attitude, anxiety, persistence, self-belief.

Table 5: Study efforts: fraction of topics completed in MyLab

Method: Probit	All topics completed			
	(1)	(2)	(3)	(4)
Always delayed or switch when delayed is €1100		*Reference*		
Switch when delayed is €1250	-0.038	-0.023	-0.012	-0.011
	(0.034)	(0.034)	(0.034)	(0.033)
Always Immediate	-0.125***	-0.101***	-0.088**	-0.093***
	(0.035)	(0.036)	(0.037)	(0.035)
Mathematics major		0.002	-0.020	-0.005
		(0.035)	(0.034)	(0.034)
Score on math entry test= 0 to 3			*Reference*	
Score on math entry test= 4 to 5		0.006	0.008	0.004
		(0.063)	(0.061)	(0.059)
Score on math entry test= 6 to 7		0.064	0.064	0.048
		(0.067)	(0.067)	(0.063)
Score on math entry test= 8 to 9		0.091	0.076	0.070
		(0.070)	(0.068)	(0.066)
Score on math entry test= 10 to 11		0.261***	0.234***	0.228***
		(0.085)	(0.084)	(0.083)
Score on math entry test= 12 to 14		0.203*	0.161	0.178*
		(0.108)	(0.105)	(0.108)
Score on statistics entry test= 0			*Reference*	
Score on statistics entry test= 1		-0.007	-0.002	0.000
		(0.050)	(0.050)	(0.048)
Score on statistics entry test=2		0.033	0.025	0.026
		(0.052)	(0.051)	(0.050)
Score on statistics entry test= 3		0.013	0.030	0.043
		(0.054)	(0.056)	(0.056)
Score on statistics entry test=4		-0.002	-0.004	0.020
		(0.063)	(0.061)	(0.064)
Score on statistics entry test= 5		0.073	0.138	0.156
		(0.100)	(0.109)	(0.113)
Score on statistics entry test= 6 to 7		-0.016	-0.040	-0.057
		(0.127)	(0.115)	(0.100)
Summer course				0.030
				(0.040)
Demographics	yes	yes	yes	yes
Personality	no	no	yes	yes
Study effort	no	no	no	yes
Observations	766	766	766	766
Pseudo r2	0.07	0.10	0.15	0.18

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1.
Control variables:
Demographics: gender, age nationality, study program, and whether the tutor is staff member or teaching assistant.
Personality: risk attitude, anxiety, persistence, self-belief.
Study effort: We include separate dummies for each quintile of the distributions of time in MyLab and number of exercises generated by MyLab, respectively.

Table 6: Study efforts: participation in summer course

Method: Probit (1=participation)	Participation in summer course			
			Sample: Math major	Sample: Math minor
	(1)	(2)	(3)	(4)
Always delayed or switch when delayed is €1100	*Reference*			
Switch when delayed is €1250	-0.004	-0.006	-0.054*	0.029
	(0.032)	(0.032)	(0.033)	(0.045)
Always Immediate	0.014	0.005	-0.056*	0.051
	(0.038)	(0.037)	(0.033)	(0.053)
Mathematics major		-0.098***		
		(0.027)		
Demographics	yes	yes	yes	yes
Personality	no	yes	yes	yes
Observations	766	766	262	504
Observations dep. var.=1	154	154	34	120
Observations dep. var.=0	612	612	228	384
Pseudo R2	0.08	0.11	0.16	0.10

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1.
Control variables:
Demographics: gender, age nationality, and study program.
Personality: risk attitude, anxiety, persistence, self-belief.

Table 7: Performance: grade final exam in QM1

Method: Tobit	Grade final exam in QM1					
	(1)	(2)	(3)	(4)	(5)	(6)
Always delayed or switch when delayed is €1100			*Reference*			
Switch when delayed is €1250	-0.370*	-0.191	-0.163	-0.211	-0.138	-0.081
	(0.218)	(0.194)	(0.189)	(0.185)	(0.169)	(0.160)
Always Immediate	-1.147***	-0.738***	-0.610***	-0.562***	-0.401**	-0.325*
	(0.234)	(0.213)	(0.209)	(0.203)	(0.185)	(0.174)
Mathematics major		0.902***	0.795***	0.792***	0.676***	0.529***
		(0.188)	(0.189)	(0.188)	(0.169)	(0.155)
Score on math entry test= 0 to 3				*Reference*		
Score on math entry test= 4 to 5		0.633**	0.680**	0.704**	0.492*	0.337
		(0.291)	(0.297)	(0.290)	(0.266)	(0.264)
Score on math entry test= 6 to 7		1.030***	0.975***	0.932***	0.588**	0.341
		(0.291)	(0.299)	(0.296)	(0.268)	(0.266)
Score on math entry test= 8 to 9		1.891***	1.823***	1.715***	1.197***	0.660**
		(0.305)	(0.310)	(0.308)	(0.282)	(0.287)
Score on math entry test= 10 to 11		2.661***	2.543***	2.421***	1.710***	1.204***
		(0.346)	(0.347)	(0.348)	(0.318)	(0.321)
Score on math entry test= 12 to 14		2.661***	2.490***	2.441***	1.815***	1.010**
		(0.458)	(0.481)	(0.486)	(0.441)	(0.431)
Score on statistics entry test= 0				*Reference*		
Score on statistics entry test= 1		-0.211	-0.187	-0.133	0.079	0.135
		(0.266)	(0.265)	(0.261)	(0.240)	(0.231)
Score on statistics entry test=2		-0.384	-0.318	-0.329	-0.179	-0.024
		(0.260)	(0.260)	(0.256)	(0.240)	(0.231)
Score on statistics entry test= 3		-0.027	0.076	0.062	0.144	0.252
		(0.282)	(0.280)	(0.276)	(0.258)	(0.244)
Score on statistics entry test=4		0.260	0.317	0.407	0.450	0.477*
		(0.348)	(0.345)	(0.326)	(0.291)	(0.276)
Score on statistics entry test= 5		0.829*	0.924**	0.889**	0.851**	0.899**
		(0.449)	(0.431)	(0.430)	(0.398)	(0.411)
Score on statistics entry test= 6 to 7		1.979**	1.867**	1.590*	1.622**	1.485**
		(0.883)	(0.812)	(0.835)	(0.779)	(0.742)
Expected grade						0.720***
						(0.093)
Demographics	yes	yes	yes	yes	yes	yes
Personality	no	no	yes	yes	yes	yes
Study effort	no	no	no	yes	yes	yes
Fraction of topics completed in MyLab	no	no	no	no	yes	yes
Observations	761	761	761	761	761	761
Pseudo r2	0.02	0.07	0.08	0.09	0.14	0.16

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1.
The dependent variable is final exam grades. Grades obtained in resit exams are excluded.
Control variables:
Demographics: gender, age nationality, study program, and whether the tutor is staff member or teaching assistant
Personality: risk attitude, anxiety, persistence, self-belief
Study effort: An indicator variable on participation in the summer course, time in MyLab and number of exercises generated by MyLab. For the latter two variables, we include a separate dummy for each quintile of the distribution.
Fraction of topics completed in MyLab: we include dummies for 5 categories.

Table 8: Performance: probability of failing exam in QM1

Method: Probit (1=fail, 0=pass)	Failed final exam in QM1					
	(1)	(2)	(3)	(4)	(5)	(6)
Always delayed or switch when delayed is €1100			*Reference*			
Switch when delayed is €1250	0.036	0.013	0.012	0.027	0.013	0.008
	(0.036)	(0.034)	(0.033)	(0.032)	(0.029)	(0.028)
Always Immediate	0.134***	0.079*	0.063	0.055	0.033	0.027
	(0.045)	(0.042)	(0.041)	(0.039)	(0.034)	(0.032)
Mathematics major		-0.131***	-0.122***	-0.127***	-0.094***	
		(0.029)	(0.029)	(0.028)	(0.023)	
Score on math entry test= 0 to 3				*Reference*		
Score on math entry test= 4 to 5		-0.084**	-0.087**	-0.089**	-0.059*	-0.047
		(0.039)	(0.038)	(0.036)	(0.032)	(0.032)
Score on math entry test= 6 to 7		-0.123***	-0.115***	-0.103***	-0.065**	-0.048
		(0.037)	(0.037)	(0.036)	(0.033)	(0.033)
Score on math entry test= 8 to 9		-0.202***	-0.196***	-0.176***	-0.122***	-0.091***
		(0.031)	(0.031)	(0.031)	(0.029)	(0.031)
Score on math entry test= 10 to 11		-0.199***	-0.190***	-0.170***	-0.118***	-0.094***
		(0.026)	(0.026)	(0.027)	(0.026)	(0.029)
Score on math entry test= 12 to 14		-0.199***	-0.189***	-0.175***	-0.137***	-0.122***
		(0.019)	(0.019)	(0.018)	(0.017)	(0.018)
Score on statistics entry test= 0				*Reference*		
Score on statistics entry test= 1		0.064	0.065	0.051	0.026	0.028
		(0.053)	(0.054)	(0.052)	(0.044)	(0.044)
Score on statistics entry test=2		0.040	0.039	0.041	0.032	0.021
		(0.053)	(0.053)	(0.052)	(0.047)	(0.045)
Score on statistics entry test= 3		0.061	0.055	0.054	0.044	0.037
		(0.057)	(0.056)	(0.056)	(0.050)	(0.049)
Score on statistics entry test=4		0.044	0.037	0.024	0.024	0.021
		(0.068)	(0.066)	(0.062)	(0.056)	(0.054)
Score on statistics entry test= 5		-0.081	-0.079	-0.049	-0.036	-0.042
		(0.077)	(0.073)	(0.078)	(0.068)	(0.070)
Score on statistics entry test= 6 to 7		-0.082	-0.075	-0.044	-0.025	-0.022
		(0.101)	(0.093)	(0.109)	(0.113)	(0.112)
Expected grade						-0.061***
						(0.017)
Demographics	yes	yes	yes	yes	yes	yes
Personality	no	no	yes	yes	yes	yes
Study effort	no	no	no	yes	yes	yes
Fraction of topics completed in MyLab	no	no	no	no	yes	yes
Observations	761	761	761	761	761	761
Pseudo r2	0.04	0.16	0.18	0.23	0.32	0.34

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1.
The dependent variable is whether a student passed or failed the final exam in QM1. Resit exam results are excluded.
Control variables:
Demographics: gender, age nationality, study program, and whether the tutor is staff member or teaching assistant
Personality: risk attitude, anxiety, persistence, self-belief
Study effort: An indicator variable for participation in the summer course, time in MyLab and number of exercises generated by MyLab. For the latter two variables, we include a separate dummy for each quintile of the distribution.
Fraction of topics completed in MyLab: we include dummies for 5 categories.

Table 9: Performance: GPA in all courses except for QM1

Method: OLS	GPA of final exams in all courses except QM1					
	(1)	(2)	(3)	(4)	(5)	(6)
Always delayed or switch when delayed is €1100			*Reference*			
Switch when delayed is €1250	-0.081	-0.014	0.010	-0.014	0.017	0.042
	(0.106)	(0.101)	(0.099)	(0.100)	(0.093)	(0.088)
Always Immediate	-0.533***	-0.384***	-0.308***	-0.289***	-0.207**	-0.175*
	(0.115)	(0.114)	(0.112)	(0.111)	(0.101)	(0.097)
Mathematics major		0.133	0.078	0.095	0.042	-0.039
		(0.096)	(0.095)	(0.098)	(0.089)	(0.085)
Score on math entry test= 0 to 3				*Reference*		
Score on math entry test= 4 to 5		0.215	0.243	0.252*	0.133	0.057
		(0.154)	(0.154)	(0.152)	(0.139)	(0.144)
Score on math entry test= 6 to 7		0.273*	0.244	0.238	0.043	-0.076
		(0.155)	(0.155)	(0.157)	(0.143)	(0.148)
Score on math entry test= 8 to 9		0.630***	0.595***	0.557***	0.285*	0.027
		(0.161)	(0.162)	(0.164)	(0.150)	(0.157)
Score on math entry test= 10 to 11		1.120***	1.046***	1.014***	0.643***	0.400**
		(0.179)	(0.178)	(0.181)	(0.171)	(0.173)
Score on math entry test= 12 to 14		0.905***	0.828***	0.812***	0.439**	0.046
		(0.220)	(0.228)	(0.235)	(0.216)	(0.220)
Score on statistics entry test= 0				*Reference*		
Score on statistics entry test= 1		-0.006	0.010	0.032	0.136	0.159
		(0.143)	(0.141)	(0.141)	(0.132)	(0.125)
Score on statistics entry test=2		0.007	0.041	0.054	0.118	0.191
		(0.145)	(0.143)	(0.143)	(0.135)	(0.127)
Score on statistics entry test= 3		0.189	0.248*	0.255*	0.290**	0.331**
		(0.149)	(0.148)	(0.149)	(0.140)	(0.132)
Score on statistics entry test=4		0.294*	0.327*	0.387**	0.398***	0.399***
		(0.173)	(0.169)	(0.164)	(0.154)	(0.144)
Score on statistics entry test= 5		0.305	0.339	0.350	0.344	0.350
		(0.244)	(0.232)	(0.241)	(0.221)	(0.221)
Score on statistics entry test= 6 to 7		0.798**	0.726**	0.644**	0.650**	0.531*
		(0.376)	(0.331)	(0.325)	(0.310)	(0.277)
Expected grade						0.350***
						(0.050)
Demographics	yes	yes	yes	yes	yes	yes
Personality	no	no	yes	yes	yes	yes
Study effort	no	no	no	yes	yes	yes
Fraction of topics completed in MyLab	no	no	no	no	yes	yes
Observations	766	766	766	766	766	766
Pseudo r2	0.10	0.19	0.23	0.26	0.38	0.44

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1.
The dependent variable is a student's GPA of final exams n all courses except QM1. Resit exam results are excluded.
Control variables:
Demographics: gender, age, nationality, and study program.
Personality: risk attitude, anxiety, persistence, self-belief
Study effort: An indicator variable for participation in the summer course, time in MyLab and number of exercises generated by MyLab.
For the latter two variables, we include a separate dummy for each quintile of the distribution.
Fraction of topics completed in MyLab: we include dummies for 5 categories.

Table 10: Impatience and first-year academic performance

Method:	Neg. Binomial Regression		Probit		Ols	Probit	
Dependent Variable:	**Number of failed final exams**		**Obtained all ECTS**		**Number of ECTS (if <60)**	**Received negative BSA**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Always delayed or switch when delayed is €1100				*Reference*			
Switch when delayed is €1250	0.029	-0.012	0.020	0.042	2.162	-0.035	-0.047*
	(0.116)	(0.113)	(0.042)	(0.043)	(2.287)	(0.027)	(0.024)
Always Immediate	0.440***	0.308**	-0.121**	-0.064	2.102	0.023	-0.012
	(0.127)	(0.124)	(0.048)	(0.051)	(2.089)	(0.032)	(0.027)
Mathematics major		-0.175		0.040	3.401*		-0.062***
		(0.110)		(0.043)	(1.939)		(0.023)
Score on math entry test= 0 to 3			*Reference*				
Score on math entry test= 4 to 5		-0.238		0.073	-1.088		0.004
		(0.171)		(0.071)	(2.758)		(0.038)
Score on math entry test= 6 to 7		-0.197		0.103	0.002		0.001
		(0.171)		(0.069)	(2.964)		(0.038)
Score on math entry test= 8 to 9		-0.405**		0.204***	0.649		-0.047
		(0.179)		(0.067)	(3.037)		(0.034)
Score on math entry test= 10 to 11		-0.899***		0.206***	4.720		-0.055*
		(0.204)		(0.070)	(3.474)		(0.033)
Score on math entry test= 12 to 14		-0.457*		0.231***	8.588**		-0.094***
		(0.260)		(0.085)	(3.935)		(0.025)
Score on statistics entry test= 0			*Reference*				
Score on statistics entry test= 1		-0.013		0.006	-2.708		0.013
		(0.152)		(0.062)	(2.716)		(0.037)
Score on statistics entry test=2		-0.109		-0.011	1.116		0.002
		(0.155)		(0.063)	(2.613)		(0.037)
Score on statistics entry test= 3		-0.241		0.008	-1.714		0.016
		(0.162)		(0.065)	(2.785)		(0.040)
Score on statistics entry test=4		-0.414**		0.011	3.918		-0.033
		(0.197)		(0.077)	(3.347)		(0.036)
Score on statistics entry test= 5		-0.445		0.039	5.474		
		(0.285)		(0.104)	(4.780)		
Score on statistics entry test= 5 to 7							-0.078***
							(0.028)
Score on statistics entry test= 6 to 7		-0.829*		0.382***	9.139*		
		(0.471)		(0.071)	(5.294)		
Demographics	yes	yes	yes	yes	yes	yes	yes
Personality	no	yes	no	yes	yes	no	yes
Study effort	no	no	no	no	no	no	no
Fraction of topics completed in MyLab	no	no	no	no	no	no	no
Observations	766	766	766	766	345	766	766
Pseudo r2	0.01	0.04	0.03	0.09	0.13	0.03	0.11

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. In columns (1) and (2), the dependent variable is the number of final exams failed, excluding the course QM1 and resit exams. In column (7), we merge the two top categories for the score on the statistics entry test, as the top category predicts failure perfectly.
Control variables:
Demographics: gender, age, nationality, and study program.
Personality: risk attitude, anxiety, persistence, self-belief

Table 11: Estimation results by ability

	Study Effort		Results in QM1		Results in other courses			
Dependent variable	Total hours logged in in MyLab	Number of exercises generated	Grade QM1	Probability of failing exam QM1	GPA	Number of failed exams	ECTS	probability of negative BSA
Method	quantile reg.	quantile reg.	tobit	probit	ols	neg. binomial	probit	probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High ability (score on math entrytest >8)								
Always delayed or switch when delayed is €1100	*Reference*							
Switch when delayed is €1250	-0.033	7.542	0.039	0.026	0.082	-0.113	0.117*	-0.025
	(3.746)	(19.146)	(0.362)	(0.021)	(0.182)	(0.261)	(0.071)	(0.026)
Always Immediate	-3.645	17.367	-1.102***	0.100	-0.570**	0.569*	-0.069	-0.016
	(4.889)	(24.991)	(0.393)	(0.065)	(0.246)	(0.312)	(0.099)	(0.029)
Observations	235	235	233	214	235	235	235	235
Medium ability (score on math entry test from 6 to 8)								
Always delayed or switch when delayed is €1100	*Reference*							
Switch when delayed is €1250	2.219	-34.419	0.120	-0.074	0.003	-0.056	0.023	-0.040
	(3.259)	(25.946)	(0.301)	(0.048)	(0.168)	(0.190)	(0.072)	(0.035)
Always Immediate	4.933	-5.213	-0.285	0.031	-0.136	0.191	-0.066	0.006
	(3.540)	(28.186)	(0.329)	(0.055)	(0.179)	(0.199)	(0.078)	(0.042)
Observations	290	290	290	290	290	290	290	290
Low ability (score on math entrytest<6)								
Always delayed or switch when delayed is €1100	*Reference*							
Switch when delayed is €1250	4.749	36.027	-0.480	0.084	-0.046	0.052	0.030	-0.081
	(5.221)	(29.726)	(0.304)	(0.082)	(0.183)	(0.168)	(0.084)	(0.054)
Always Immediate	1.131	70.602**	-0.693**	0.086	-0.312	0.251	-0.065	-0.069
	(5.705)	(32.480)	(0.342)	(0.090)	(0.192)	(0.179)	(0.089)	(0.055)
Observations	241	241	238	235	241	241	235	238

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. Coefficients of probit models report mean marginal effects. Quantile regressions use the median. In all regressions, we control for age, gender, nationality, study program, whether the tutor is a staff member (in case of QM1), entry test scores on mathematics and statistics (dummies as in the analyses on the whole sample), pre-education, risk attitude, anxiety, persistence, and self-belief.

Table 12: Differences in learning styles

Method:	Quantile reg.	Probit	Quantile regression			
Dependent Variable:	**Time per exercise**	**All topics completed**	**Guided Solutions**	**Sample Problems**	**Guided Solutions per exercise**	**Sample problems per exercise**
	(1)	(2)	(3)	(4)	(5)	(6)
Always delayed or switch when delayed is €1100			*Reference*			
Switch when delayed is €1250	0.01***	-0.01	-8.31	8.87	0.00	0.01
	(0.00)	(0.03)	(6.56)	(9.69)	(0.01)	(0.02)
Always Immediate	-0.01**	-0.10***	-3.82	0.02	-0.02	0.03
	(0.00)	(0.03)	(7.93)	(10.96)	(0.01)	(0.02)
Mathematics major	0.01**	-0.01	-16.79***	-36.86***	-0.01	-0.03*
	(0.00)	(0.03)	(6.00)	(9.46)	(0.01)	(0.02)
Time per exercise first quintile		*Reference*				
Time per exercise second quintile		-0.04				
		(0.05)				
Time per exercise third quintile		0.05				
		(0.07)				
Time per exercise fourth quintile		0.07				
		(0.10)				
Time per exercise fifth quintile		0.07				
		(0.14)				
Score on entry tests math and statistics	yes	yes	yes	yes	yes	yes
Demographics	yes	yes	yes	yes	yes	yes
Personality	yes	yes	yes	yes	yes	yes
Study effort	no	yes	no	no	yes	yes
Observations	763	763	737	737	735	735
Pseudo r2	0.06	0.19	0.04	0.10	0.10	0.15

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. The quantile used in the regressions is the median. In column (2), the estimation method is probit. The dependent variable takes the value one if all topics are completed and zero otherwise.
Control variables:
Score on entry tests math and statistics: we include a separate dummy for 6 (7) categories of the math (statistics) entry test.
Demographics: gender, age, nationality, and study program.
Personality: risk attitude, anxiety, persistence, self-belief
Study effort: An indicator variable on participation in the summer course, time in MyLab and number of exercises generated by MyLab. For the latter two variables, we include a separate dummy for each quintile of the distribution.

Table 13: study effort by weekly problem set

Method: Quantile Regression	Hours logged in to MyLab by weekly problem set						
	week 1	week 2	week 3	week 4	week 5	week 6	week 7
Always delayed or switch when delayed is €1100				*Reference*			
Switch when delayed is €1250	-0.189	-0.048	0.424	0.892*	0.807*	0.416	-0.179
	(0.273)	(0.198)	(0.376)	(0.529)	(0.457)	(0.256)	(0.355)
Always Immediate	0.117	0.005	-0.384	0.149	-0.035	0.342	-1.038**
	(0.303)	(0.211)	(0.393)	(0.493)	(0.491)	(0.276)	(0.428)
Observations	766	766	766	766	766	766	766
Pseudo r2	0.13	0.08	0.12	0.10	0.12	0.1	0.07

Method: Quantile Regression	Number of exercises generated by weekly problem set						
	week 1	week 2	week 3	week 4	week 5	week 6	week 7
Always delayed or switch when delayed is €1100				*Reference*			
Switch when delayed is €1250	-1.211	0.337	1.794	0.683	-0.158	1.376*	-1.645
	(1.332)	(0.971)	(2.001)	(2.106)	(1.604)	(0.739)	(1.703)
Always Immediate	5.799***	3.138**	4.354	0.352	5.200	4.367***	-0.761
	(2.004)	(1.374)	(3.463)	(2.640)	(3.325)	(1.171)	(1.953)
Observations	766	766	766	766	766	766	766
Pseudo r2	0.07	0.04	0.04	0.03	0.05	0.03	0.03

Method: probit (1=all topics completed)	All topics completed by weekly problem set						
	week 1	week 2	week 3	week 4	week 5	week 6	week 7
Always delayed or switch when delayed is €1100				*Reference*			
Switch when delayed is €1250	-0.055	-0.098**	-0.055	-0.080*	-0.062	-0.070	-0.016
	(0.038)	(0.042)	(0.043)	(0.044)	(0.043)	(0.044)	(0.037)
Always Immediate	-0.045	-0.054	-0.089*	-0.071	-0.134***	-0.086*	-0.059
	(0.046)	(0.051)	(0.051)	(0.052)	(0.049)	(0.052)	(0.043)
Observations	766	766	766	766	766	766	766
Pseudo r2	0.19	0.14	0.15	0.12	0.15	0.13	0.14

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. Coefficients of probit models report mean marginal effects. Quantile regressions use the median. In all regressions, we control for age, gender, nationality, study program, whether the tutor is a staff member (in case of QM1), entry test scores on mathematics and statistics (dummies as in the analyses on the whole sample), mathematics major, risk attitude, anxiety, persistence, and self-belief.

Table 14: individual fixed-effects regressions of study efforts by weekly problem set

Method: Fixed-effects regression	**Hours logged into MyLab by weekly problem set**	**Number of exercises by weekly problem set**	**Fraction of topics completed by weekly problem set**
	(1)	(2)	(3)
week 2 * Switch when delayed is €1250	0.023	1.068	0.000
	(0.265)	(1.953)	(0.008)
week 3 * Switch when delayed is €1250	0.272	0.973	0.016
	(0.357)	(3.146)	(0.011)
week 4 * Switch when delayed is €1250	0.655	1.547	0.019
	(0.449)	(2.929)	(0.014)
week 5* Switch when delayed is €1250	0.765	-1.687	0.014
	(0.495)	(2.908)	(0.017)
week 6 * Switch when delayed is €1250	0.258	1.375	0.026
	(0.347)	(2.580)	(0.019)
week 7 * Switch when delayed is €1250	-0.158	-1.781	0.004
	(0.420)	(2.883)	(0.021)
week 2 * Always Immediate	-0.131	-3.393	-0.004
	(0.314)	(2.097)	(0.008)
week 3 * Always Immediate	0.122	2.543	0.001
	(0.437)	(4.067)	(0.013)
week 4 * Always Immediate	-0.610	-3.093	-0.015
	(0.507)	(4.298)	(0.018)
week 5 * Always Immediate	-0.254	-0.438	-0.039*
	(0.597)	(4.030)	(0.023)
week 6 * Always Immediate	-0.476	-2.572	-0.034
	(0.400)	(3.381)	(0.026)
week 7 * Always Immediate	-1.467***	-8.558**	-0.064**
	(0.484)	(3.617)	(0.028)
Individual fixed effects	yes	yes	yes
Week fixed effects	yes	yes	yes
Week fixed effects * Math entry test score	yes	yes	yes
Week fixed effects * Math major	yes	yes	yes
Observations	5,362	5,362	5,362
Number of individuals	766	766	766
r2	0.39	0.34	0.19

Heteroskedasticity robust standard errors in parentheses. Stars indicate significance as follows: ***p<0.01, **p<0.05, *p<0.1. All regressions include individual and week fixed effects.

Appendix: Figures

Figure A1: Distribution of time preferences

Figure A2: Distribution of entry test scores mathematics

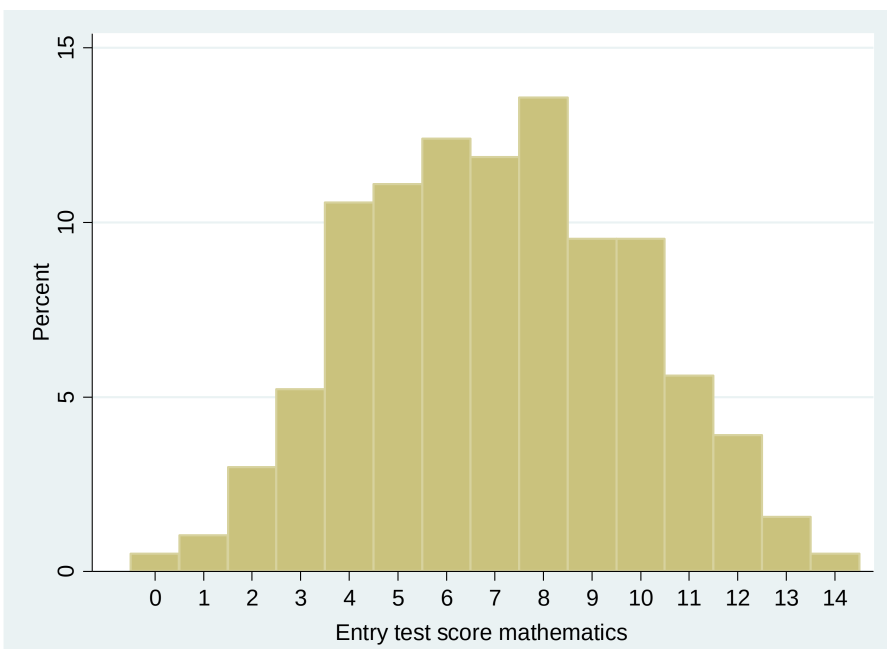

Figure A3: Distribution of time logged in to MyLab

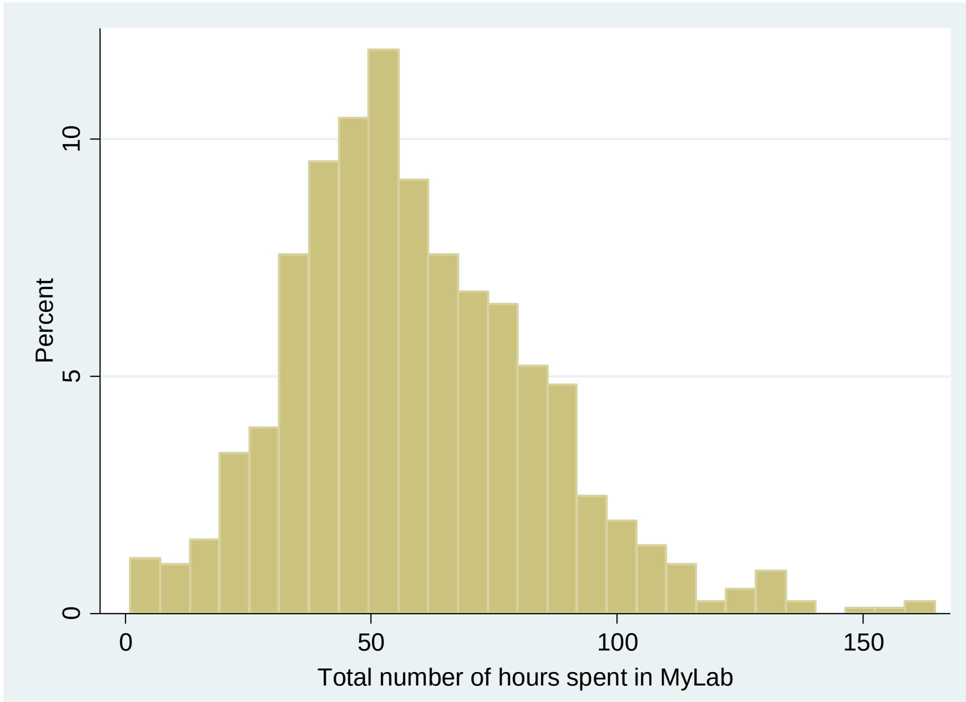

Figure A4: Distribution of number of exercises generated by MyLab

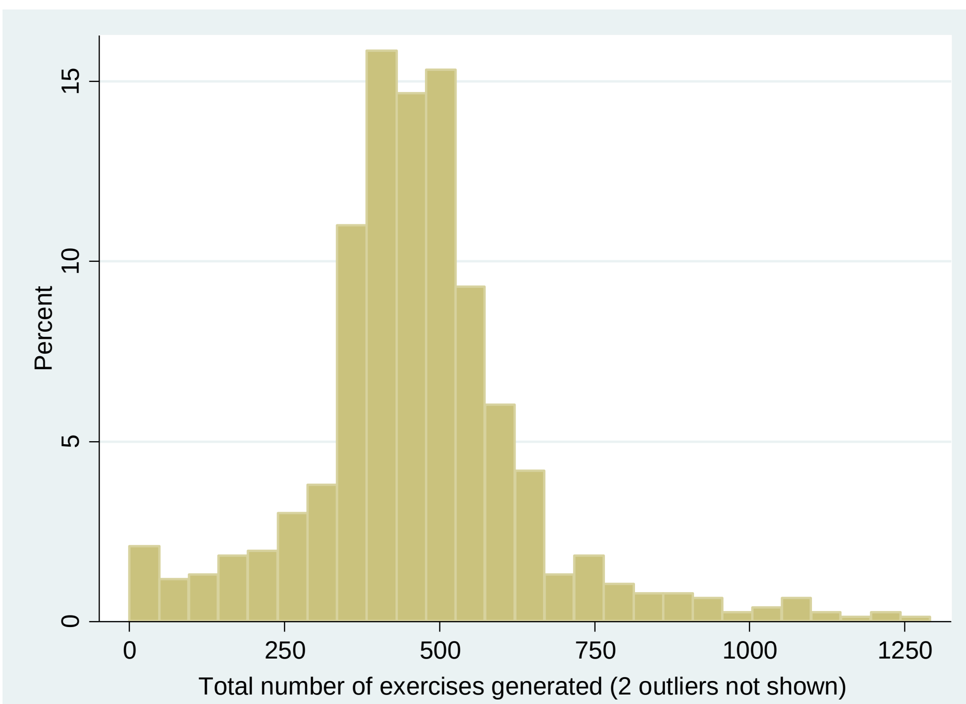

Figure A5: Distribution of fraction of topics completed

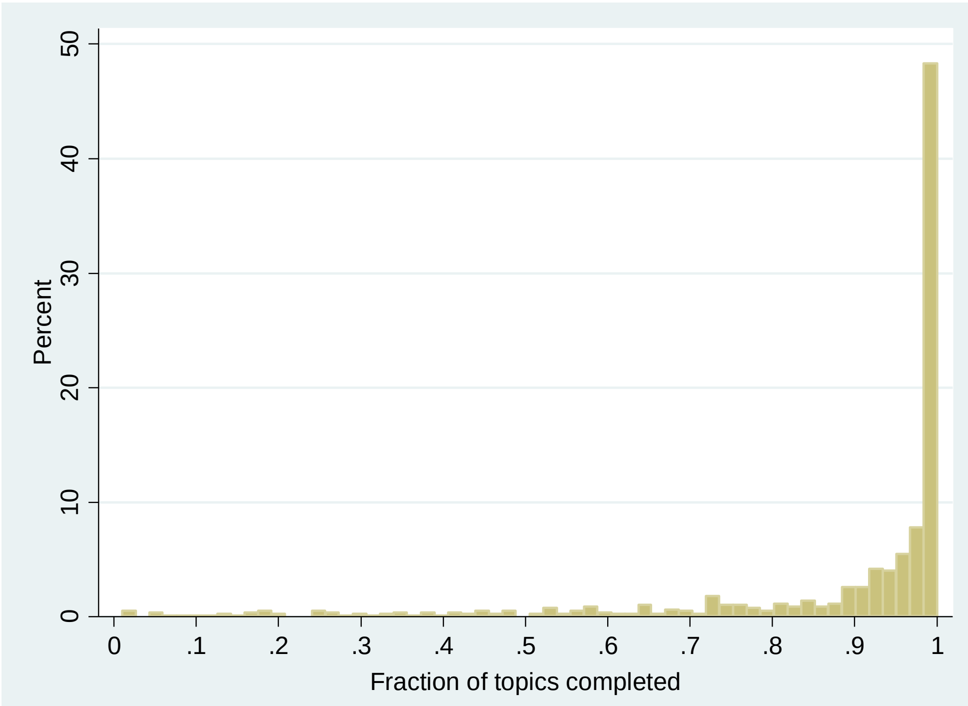

Figure A6: Distribution of final exam grades in QM1

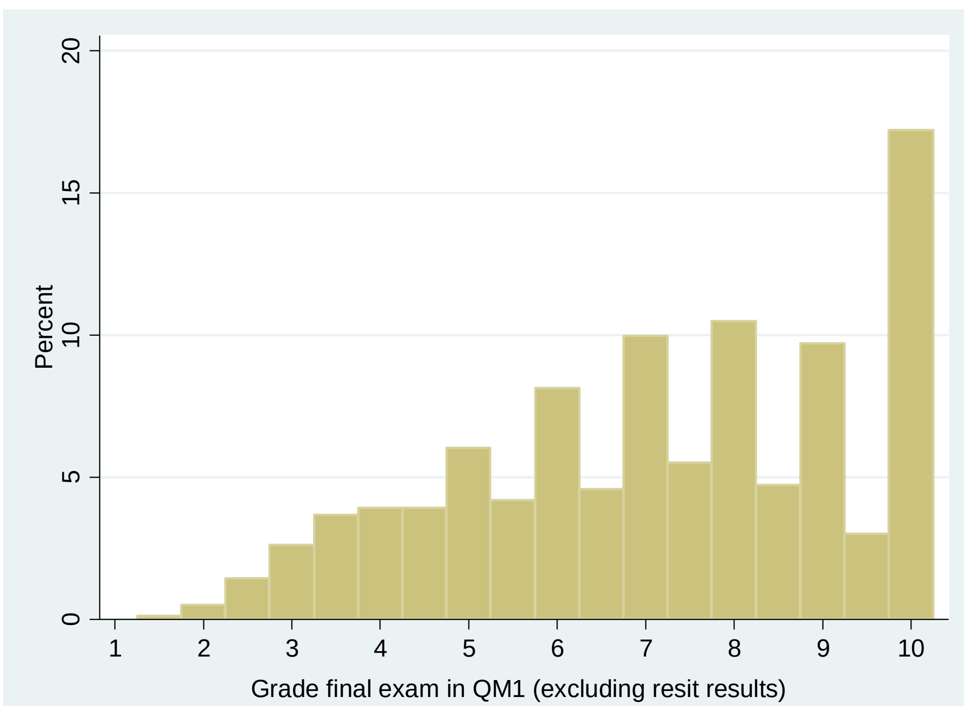

Figure A7: Distribution of GPA final exams (excluding grade QM1 and resits)

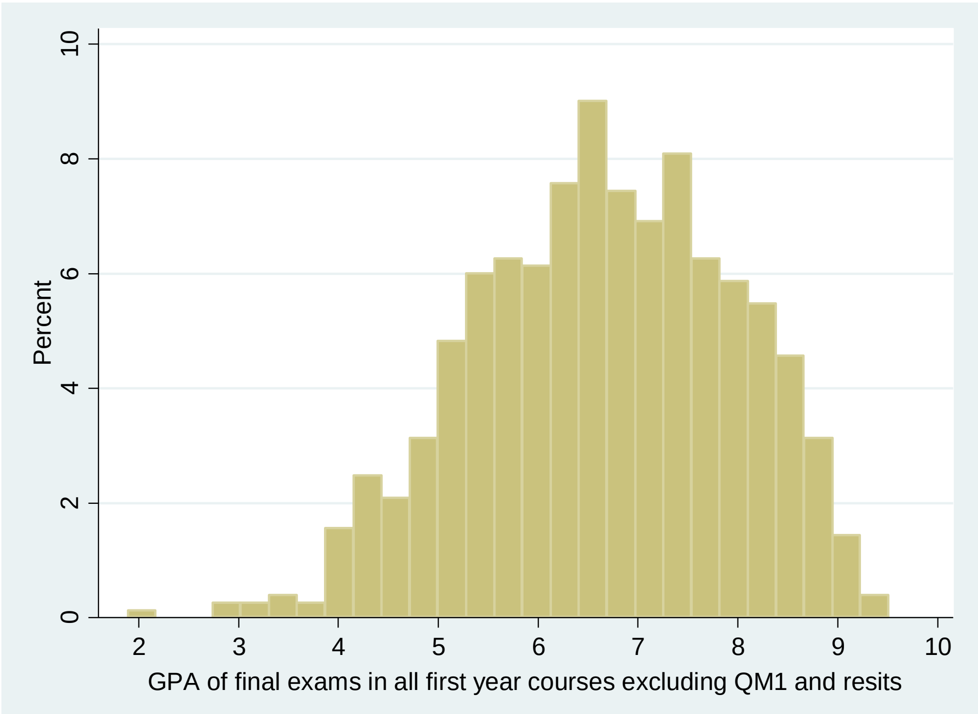

Figure A8: Distribution of the number of failed final exams (excluding exam results in QM1 and resits)

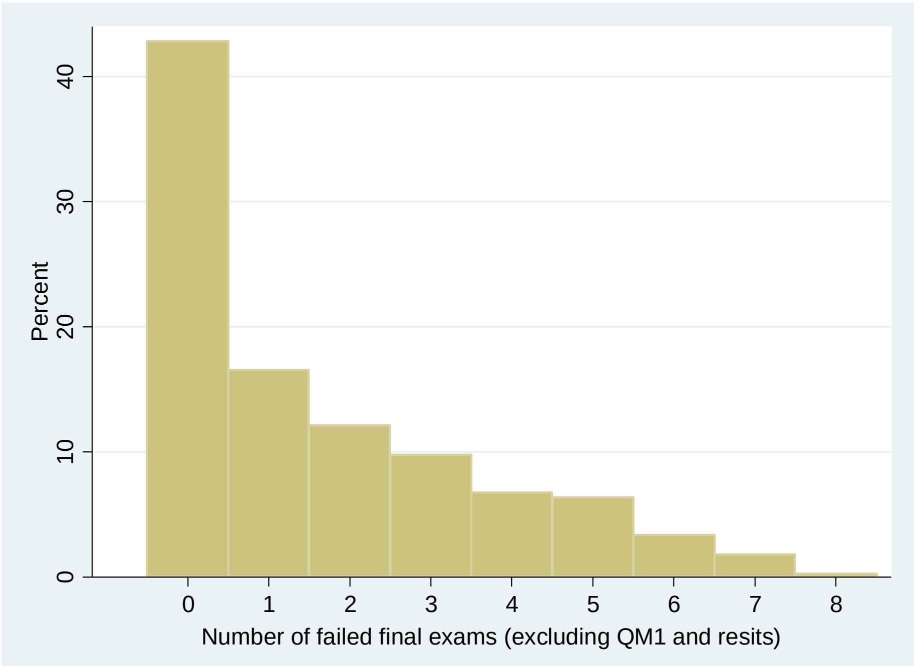

Figure A9: Distribution of study credits (ECTS) earned

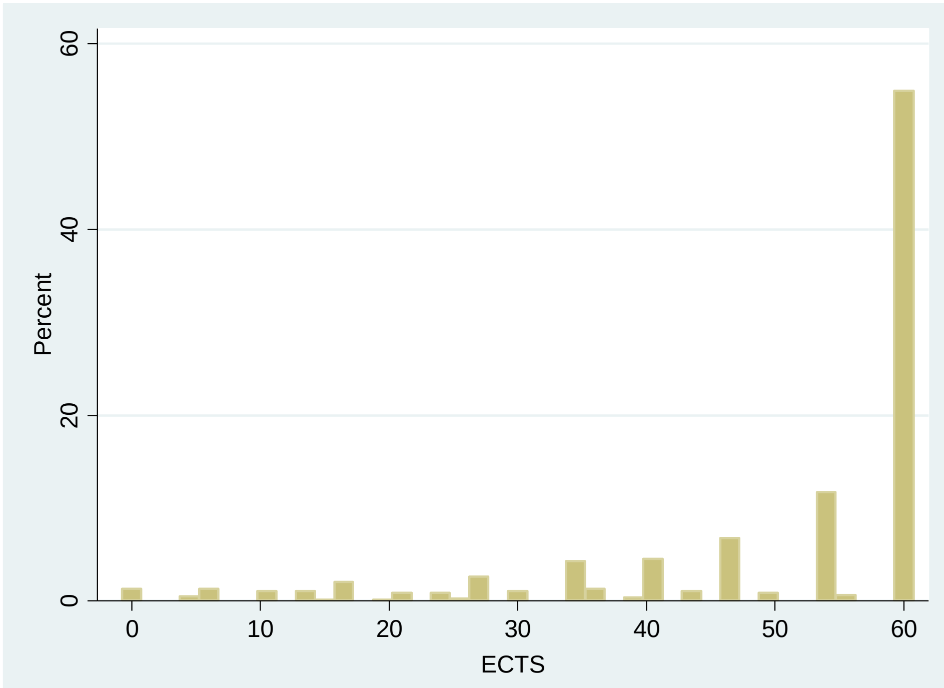

Figure A10: distribution of requests for a guided solution in MyLab ("Help me solve this")

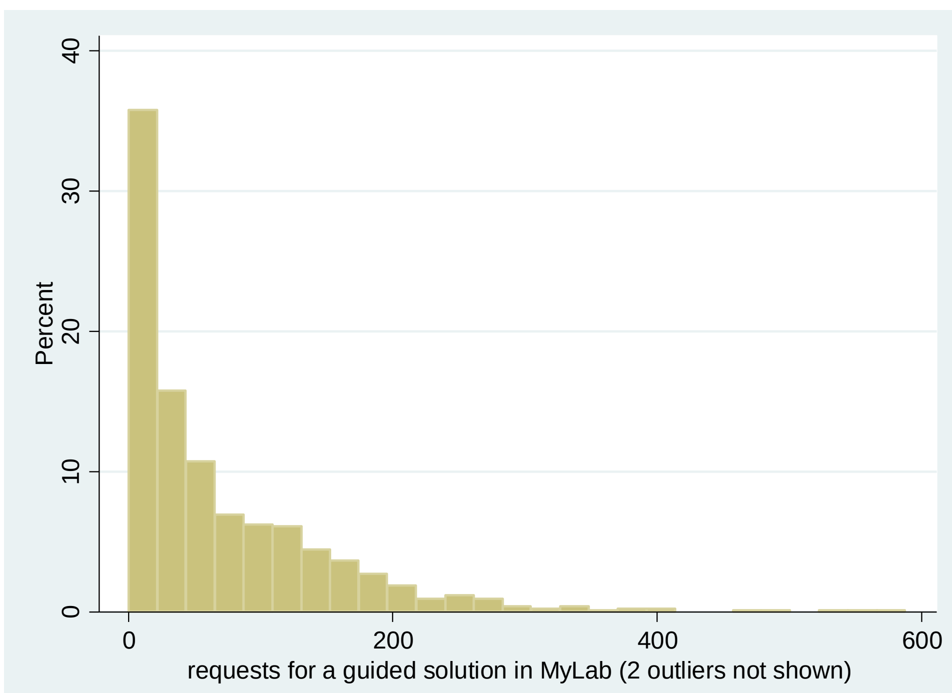

Figure A11: distribution of sample problems generated by MyLab in the final attempt ("View an Example")