Erschienen in: Economics of Education Review. 2019, 72, S. 66-79
https://doi.org/10.1016/j.econedurev.2019.04.004

Young, gifted and lazy? The role of ability and labor market prospects in student effort decisions[☆]

Adrian Chadi[*,a], Marco de Pinto[b,c], Gabriel Schultze[b]

[a] *University of Konstanz, P.O. Box 131, Universitätsstr. 10, Konstanz 78457, Germany*
[b] *Institute for Labour Law and Industrial Relations in the European Union (IAAEU), Trier University, Behringstr. 21, Trier 54296, Germany*
[c] *IUBH University of Applied Science, IUBH Fernstudium, Kaiserplatz 1, Bad Reichenhall 83435, Germany*

A R T I C L E I N F O

Keywords:
Higher education
Effort
Study time
Leisure
Ability
Labor market data

JEL classification:
I23
J22
J24

A B S T R A C T

This paper examines the decision-making process of students from an economic perspective to understand the determinants of an individual's willingness to provide effort. Our theoretical model predicts that ability and job market prospects are positive determinants. Analyzing a novel dataset on thousands of German students, however, we instead find that ability has a significantly negative effect on effort. It seems that the marginal gain of increasing effort in terms of higher expected income after studying is lower for high-ability students compared to low-ability students. In regard to the second determinant, the evidence rejects a similar argument, according to which great job market prospects may impair student effort. Applying an instrumental variable approach based on official unemployment data on regional labor markets, we can confirm our prediction on the positive role of perceived employment prospects in actual student behavior.

1. Introduction

The circumstances under which individuals strive are central to scientific research on human behavior. The economic approach suggests that individuals provide high efforts whenever the expected benefits of an activity exceed the expected costs. However, we know little about the determinants of effort outside of experimental laboratories. Similarly, situations when individuals – instead of providing high efforts to maximize their economic gain – make the decision to simply lean back remain largely unexplored. In some cases, individuals with particular potential and great prospects may show high motivation to provide extraordinary performance, while in other cases, a positive outlook may actually lower effort levels, as it is possible to benefit from reduced effort costs while still obtaining a satisfactory level of achievement. By focusing on students from higher education institutions, we analyze individual effort decisions, which allows us to not only shed light on the determinants of human behavior in this particular educational context, but also beyond.[1]

The decision situation faced by students in the system of higher education has a particular facet that makes it very interesting from an

☆ We are grateful for helpful comments by participants of the 8th Workshop on Economics in Trier, of the 1st NEPS User Conference in Bamberg, of the Workshop on Subjective Survey Data in Labour Market Research in Trier, of the Colloquium on Personnel Economics in Zurich, of the Royal Economic Society Annual Conference in Bristol, of the Workshop on Labor Economics in Trier, of the European Economic Association Annual Congress in Lisbon, of the IAW Workshop in Tübingen and by seminar participants in Luxembourg and Trier. We also thank two anonymous referees for their useful comments as well as Laszlo Goerke and Jochen Michaelis for inspiring discussions.

* Corresponding author.
E-mail addresses: adrian.chadi@uni-konstanz.de (A. Chadi), depinto@iaaeu.de, m.de-pinto@iubh-fernstudium.de (M. de Pinto), schultze@iaaeu.de (G. Schultze).

[1] Microeconomic models of individual effort decisions typically include assumptions on the role of an individual's potential, such as ability, without providing references to empirical evidence. This is not surprising, given a lack of studies that focus specifically on the question of how ability affects effort. While a lot of evidence on determinants of individual effort levels comes from economic laboratory experiments, researchers here oftentimes inspect mindless tasks to purposely render certain inputs like ability irrelevant. Economic researchers of field data often fall back on proxies like absenteeism (see e.g. Block, Goerke, Millán, & Román, 2014; Chadi & Goerke, 2018; Cornelißen, Himmler, & Koenig, 2011; Ichino & Riphahn, 2005), or hours worked (see Bell & Freeman, 2001), given the importance of effort and its determinants in a variety of different research contexts, as e.g. workers' performance in firms. Another option for researchers to gather evidence from the field is professional sports, which allows testing economic predictions on effort decisions in non-laboratory data (see e.g. Lackner, Stracke, Sunde, & Winter-Ebmer, 2015).

economic standpoint: Both society and the individual student benefit from educational achievement. The more educational achievement can be attained, the higher the individual labor market earnings are because of increased human capital (e.g. Chevalier, Harmon, Walker, & Zhu, 2004; Kroch & Sjoblom, 1994; Wolpin, 1977), which thereby fosters overall economic prosperity. To achieve this, students can choose individual effort levels as a major determinant of educational outcome (e.g. Stinebrickner & Stinebrickner, 2008). This leads to a scenario in which students have incentives for putting large amounts of effort into studying, benefiting both the economy and society. In reality, however, indications suggest a lack of effort levels among students, such as declining amounts of time spent on studying (e.g. Babcock & Marks, 2011) and increasing study durations in numerous countries (e.g. Bound, Lovenheim, & Turner, 2012; Brunello & Winter-Ebmer, 2003; Garibaldi, Giavazzi, Ichino, & Rettore, 2012). This raises the questions regarding the determinants of study behavior and how the drivers of students' commitment to performing well can be identified.

While there is a sizable literature on the outcomes of studying, there are not many studies dealing with economic decision-making in terms of student effort in higher education. Many of the contributions to research on educational achievement of university or college students focus on study outputs, such as grades, and analyze potential determinants, such as financial incentives or working during school (e.g. Kalenkoski & Pabilonia, 2010; Stinebrickner & Stinebrickner, 2003).[2] Few papers provide a combination of empirical analysis and theoretical modeling, in which the latter considers the crucial role of student effort as a contributor to academic success (see e.g. Bandiera, Larcinese, & Rasul, 2015; Krohn & O'Connor, 2005; Löfgren & Ohlsson, 1999).[3] One example in this context is a study by Oettinger (2002), who discusses how university students make strategic decisions on effort levels, for which he assumes that incentives to provide effort increase in ability. In their study on student performance, Leuven, Oosterbeek, and van der Klaauw (2010) also take the role of effort into account but mostly focus on passing rates and how student performance can be raised by financial incentives. Similarly, Non and Tempelaar (2016) consider both effort and academic success in their empirical study on the role of time preferences, just as Chevalier, Dolton, and Lührmann (2018) do in their study on incentive schemes. There is also recent theoretical work on the role of examination rules for students' effort decisions (Michaelis & Schwanebeck, 2016).

Apart from that, we concur with the conclusion of Delaney, Harmon, and Ryan (2013) who see a clear lack of knowledge on student inputs, despite the high level of interest in explaining study outcomes. While these authors provide the first empirical investigation into the determinants of student behavior in higher education using across-subject data, they omit two determinants that we consider to be as important as they are unclear in their actual role for effort decisions: ability and labor market prospects. Intuitively, one could expect that high-ability types have strong incentives to provide extra effort, as they benefit more from educational achievement, which also seems to be in line with the evidence from the above-mentioned studies. On the other hand, they could also use their promising situation to reduce effort when they are satisfied with a certain level of achievement. Similar arguments apply for job market prospects in general, which could also affect student behavior and help to explain low effort levels. Given the unclear relationships, we provide the first comprehensive discussion, theoretically and empirically, on how these factors affect students' effort.

As a potentially important aspect, we consider multiple dimensions of student effort in our discussion. Whereas previous educational studies often focused on study time measured via lecture attendance, the role of this factor in educational achievement appears to be unclear.[4] Given the heterogeneity of empirical findings in this context, we scrutinize whether study time is sufficient for capturing individual effort and question the underlying assumption that investing the same amount of time means investing the same amount of effort. Arguably, any given hour spent in the library or in the lecture room may consist of only focused learning, but it may just as well consist of only idle daydreaming. We therefore propose a distinction into a quantitative and a qualitative dimension of effort in order to learn more about the complex factor that effort certainly is. While in our theoretical discussion we distinguish between study time (quantitative dimension) and learning intensity (qualitative dimension), we attempt to capture the quantitative component via comprehensive time-use data and the qualitative component via subjective data on self-assessed effort levels in our empirical investigation.

In our theoretical modeling of student decision-making, we make some basic assumptions that conform to the previous literature. Students decide about both effort dimensions anticipating that higher effort is associated with a utility decline today, but improves educational achievements and hence increases expected income and utility after studying. Whether high-ability students provide less or more effort compared to low-ability students depends on two factors. First, considering each effort dimension separately, high-ability students have an incentive to increase effort, such as study time (at the expense of leisure), because this raises utility in the future, i.e. the substitution effect (SE). At the same time, however, high-ability students have an incentive to reduce effort because their high abilities per se ensure relatively good educational achievement and thus a relatively high level of expected income, i.e. the income effect (IE). Second, the way both effort dimensions are interlinked is crucial. If they were complements, high-ability students that provide high learning intensity would also choose a high study time, compared to low-ability students. If both dimensions were substitutes, however, high learning intensity would come at a price of lower study time and vice versa. These mechanisms also hold for our second determinant, i.e. job market prospects.

To gain testable predictions, we assume that both the students' utility and educational production function are of a Cobb-Douglas type. This implies that a.) the SE dominates the IE and that b.) both effort dimensions are complements. As such, we expect that high-ability students provide higher effort (study time and learning intensity) compared to low-ability students. In addition, better job market prospects should increase the students' effort in both dimensions during academic studies. The mechanisms in our model translate to many other economics contexts and thereby provide us with a general framework upon which we can discuss our empirical results. This is particularly helpful as our empirical findings for individuals in higher education do indeed deviate in some respect from expectations one may have at first glance.

To test theoretical predictions, we explore data from a broadly conceived investigation of students in Germany's system of higher education, the National Educational Panel Study (NEPS). The students'

[2] Other indicators of study outputs in the context of higher education are graduation rates (e.g. Light & Strayer, 2000) and study durations (e.g. Gunnes, Kirkebøen, & Rønning, 2013).

[3] Note that there are also some studies discussing the importance of student effort for educational achievement among pupils before they enter higher education, such as Metcalfe, Burgess, and Proud (2019) as well as De Fraja, Oliveira, and Zanchi (2010) who also point out a lack of research on the role of student effort.

[4] See Grave (2011) for a comprehensive study on the role of students' time allocation in educational achievement. While she finds rather positive relationships between the latter and both lecture attendance and self-study time for her data on German university students, Dolton, Marcenaro, and Navarro (2003) find a more positive role of attendance compared to self-study using data on Spanish university students. In contrast, Bratti and Staffolani (2013) find the opposite for Italian university students and view self-study as a more important predictor of academic performance than attendance.

cohort of the NEPS has not been utilized for similar purposes so far and allows us to inspect the role of ability, as an example, in ways not possible in most cross-subject datasets. Regarding this key student input, we can exploit data from comprehensive competence testing of university students to establish a measure that allows us to inspect this determinant of university students' behavior without having to rely on proxies such as previous grades, which are likely related to an individual's overall attitude towards providing effort. As we argue in our paper, this could be a particular problem for any attempt to find out about the actual impact of individual ability on effort. Finally, we provide evidence on the direct effects of job market prospects on student effort, as the outlook on future earnings reflects the channel through which students take their economic gains of studying into account. We thereby elaborate on the work of Brunello, Lucifora, and Winter-Ebmer (2004) who argue that subjectively expected returns to education are a key determinant for university students' decision-making regarding educational attainment.[5]

Our results from analyzing the NEPS data reject the prediction that ability positively affects effort levels. Instead, the evidence conforms to the notion that high-ability students use their advantage over low-ability ones to obtain additional utility by having more leisure time. We find that the higher the ability is, the lower self-assessed effort levels and weekly self-study hours are. As the latter predicts educational achievement in our data more strongly than the other activities, such as lecture attendance, this empirical result supports the notion of the 'lazy genius' who puts comparatively little effort into studying. Going back to our model, this speaks for a relatively strong IE and/or a relatively weak SE. Regarding job market prospects, we not only examine standard regression results but also apply an instrumental variable (IV) approach to address the potential reverse causality between effort and labor market prospects. To that end, we exploit official unemployment data reflecting variations in regional labor market conditions. We merge the data using information on prospective jobs and university location. The results from applying this approach align with those from running standard regressions and suggest that great job prospects positively influence effort, which confirms our theoretical prediction. Vice versa, we interpret our finding in such a way that not having good prospects may frustrate students, leading to decreased motivation for putting in high efforts into studying, which may contribute to the phenomenon of prolonged study durations, as argued by other researchers (e.g. Aina, Baici, & Casalone, 2011).

2. Theoretical model

2.1. Set-up

We analyze the study behavior of an individual by using a two-period model. While being a student in the present period 1, the individual expects to enter the labor market in the future period 2 to earn income. The individual's utility function is assumed to be:

$$U = V(I^1, L^1) - C(e) + \beta V(I^2, L^2), \qquad 0 < \beta \leq 1, \tag{1}$$

where I^1 (I^2) denotes income in period 1 (expected income in period 2), L^1 (L^2) represents leisure in period 1 (leisure in period 2) and β is the discount rate.[6] We assume that sub-utility V increases in income and leisure at a decreasing rate. e measures the student's learning intensity. Intuitively, e indicates how diligent the student is and how hard s/he works during the time span that s/he has scheduled for studying. Learning intensity is associated with utility costs (or disutility) measured by C, which is increasing and convex, C_e, $C_{ee} > 0$, where subscripts denote partial derivatives.

Income in period 1 is assumed to be exogenously given, while leisure in period 1 reads $L^1(s) = T - s$. The endogenous variable s represents the time that the individual spends on academic studies. Given the (exogenous) time stock T, which also summarizes the time required for other activities besides studying (e.g. student employment), s determines the amount of leisure a student has. In the literature, study time is often considered as an effort indicator. In our setup, however, s constitutes only a quantitative dimension of effort, while its qualitative dimension is captured by learning intensity e.

In period 2, expected income depends on the individual's achievement during academic studies (for a similar assumption see De Fraja & Landeras, 2006; De Fraja et al., 2010; Löfgren & Ohlsson, 1999). The student's achievement is typically represented by the educational production function (EPF). Following a large strand of literature on the determinants of study success (for an excellent review see Brewer & McEwan, 2010), we assume that the student's achievement positively depends on learning intensity e, study time s and the student's time invariant and exogenously given ability level a.

The EPF can be formalized as:

$$Y = Y(e, s, a, X), \tag{2}$$

with Y_e, Y_s, $Y_a > 0$. The vector X captures all other factors that influence Y, for example family background or the quality of the university. Note that the sign of the cross derivative Y_{se} is undetermined. As such, both effort dimensions are interrelated and can be either complements ($Y_{se} > 0$) or substitutes ($Y_{se} < 0$).

Expected income in period 2 is thus given by:

$$I^2 = \delta Y(e, s, a, X), \qquad \delta \geq 0. \tag{3}$$

The parameter δ captures the student's job market prospects. If these prospects are relatively good (bad), i.e. δ is relatively high (low), a given level of educational achievement Y implies a relatively high (low) value of expected income I^2. To disentangle the effects of a student's ability and job market prospects on her/his effort during studying, we focus on prospects that are not related to a student's ability. For example, a student's job market prospects could be determined by predictions about future labor market conditions or subjective perceptions thereof. As such, we interpret δ as a measure for non-ability-related labor market expectations and consider it as exogenously given and thus independent of a (as well as of s and e). Note that job market prospects can change over time, such that δ could increase or decrease during academic studies. Future leisure L^2 is also assumed as exogenously given.[7]

With these components at hand, we can rewrite the individual's utility function as:

$$U(s, e, \delta, a) = V(I^1, L^1(s)) - C(e) + \beta V(I^2(e, s, \delta, a)), L^2), \tag{4}$$

where we have suppressed some of the variables to save notation.

2.2. Optimization

At the beginning of period 1, the student decides about time allocation during academic studying, i.e. the student chooses how much time (of T) will be spent on studying s. The residual time is used for

[5] In a similar fashion, many researchers promote the use of subjective data on students' beliefs and expectations regarding the role of the labor market in student behavior, such as Betts (1996); Bonnard, Giret, and Lambert-Le Mener (2014); Botelho and Pinto (2004); Brodaty, Gary-Bobo, and Prieto (2014); Huntington-Klein (2015); Jensen (2010); Stinebrickner and Stinebrickner (2014); Webbink and Hartog (2004); Wolter (2000).

[6] To keep our analysis as simple as possible, we consider the discount rate as exogenously given and, in particular, independent of students' characteristics such as their abilities. For the same assumption, see, for instance, De Fraja et al. (2010).

[7] This assumption is made for simplification. It can be justified because working hours are predetermined in highly regulated labor markets such as in Germany. Moreover, an endogenous determined L^2 would not qualitatively alter our results.

leisure and other (exogenous) activities. In addition, the student sets learning intensity e. Both decisions are made to maximize total utility U.

Differentiating (4) with respect to s implies:

$$U_s = -\underbrace{V_{L^1}(s)}_{\equiv MC_S(s)} + \underbrace{\beta V_{I^2}(s, e, \delta, a)\delta Y_s(e, s, a)}_{\equiv MG_S(e,s,a,\delta)} = 0, \tag{5}$$

where MC_s and MG_s denote the marginal costs and the marginal gains of an increase in study time, respectively. This implies that study time is chosen such that the utility decrease today (due to reduced leisure) is exactly offset by the utility increase in the future (due to improved educational achievements and thus raised expected income). Note that (5) pins down the utility maximizing study time for any given level of learning intensity, ability and labor market prospects: $\bar{s} = s(e, a, \delta)$.

The first-order condition with respect to learning intensity reads:

$$U_e = -\underbrace{C_e(e)}_{\equiv MC_e(e)} + \underbrace{\beta V_{I^2}(s, e, \delta, a)\delta Y_e(e, s, a)}_{\equiv MG_e(e,s,a,\delta)} = 0, \tag{6}$$

with MC_e and MG_e representing the marginal costs and the marginal gains of an increase in e, respectively. As a result, learning intensity is chosen such that the utility decrease today (due increased costs C) is balanced by the utility increase in the future (due to improved educational achievements and thus raised expected income). Note that (6) pins down utility maximizing learning intensity for any given level of study time, ability and labor market prospects: $\bar{e} = e(s, a, \delta)$.

By combining $\bar{s}$ and $\bar{e}$, we can determine utility maximizing study time and learning intensity as functions of exogenous parameters only: $s^* = s(a, \delta)$ and $e^* = e(a, \delta)$.[8]

2.3. Comparative static analysis

How do the student's ability a and labor market prospects δ affect the student's effort choices, i.e. the utility maximizing study time and learning intensity? To provide a theoretical answer to this question, we conduct a comparative static exercise, i.e. we consider variations in δ and a.[9]

2.3.1. Abilities

Let us compare a high-ability student with a low-ability student. Totally differentiating (5) and (6) and rearranging the resulting expressions yield:

$$\frac{ds}{da} = -\frac{1}{\underbrace{U_{ss}}_{<0}}\left(U_{sa} + U_{se}(Y_{se})\frac{de}{da}\right), \tag{7}$$

$$\frac{de}{da} = -\frac{1}{\underbrace{U_{ee}}_{<0}}\left(U_{ea} + U_{se}(Y_{se})\frac{ds}{da}\right). \tag{8}$$

Partial derivatives read $U_{sa} = \beta\delta\left(V_{I^2I^2}\delta Y_a Y_s + V_{I^2} Y_{sa}\right)$, $U_{ea} = \beta\delta\left(V_{I^2I^2}\delta Y_a Y_e + V_{I^2} Y_{ea}\right)$ and $U_{se}(Y_{se}) = \beta\delta\left(V_{I^2I^2}\delta Y_e Y_s + V_{I^2} Y_{se}\right)$.

To decompose the effects on the student's behavior, we first look at the effects on $\bar{s}$ and $\bar{e}$, where $de/da = 0$ and $ds/da = 0$ hold, respectively. The sign of $d\bar{s}/da$ ($d\bar{e}/da$) depends then on the sign of U_{sa} (U_{ea}). Intuitively, there are two countervailing effects. High-ability students have higher marginal gains from effort because of an increased expected income. Therefore, they substitute leisure for study time or increase learning intensity despite the associated rise of disutility. We call this the substitution effect (SE). Given the increased expected income, however, high-ability students also have an incentive to reduce study time (learning intensity) to keep the marginal gains from s (e) constant. We call this the income effect (IE). In general, the net effect is ambiguous.

The impact on s^* and e^* can be calculated by combining (7) and (8). This yields:

$$\frac{ds^*}{da} = \frac{1}{\underbrace{|H|}_{>0}}\left(U_{se}(Y_{se})\cdot U_{ea} - \underbrace{U_{ee}}_{<0}U_{sa}\right), \tag{9}$$

$$\frac{de^*}{da} = \frac{1}{\underbrace{|H|}_{>0}}\left(U_{se}(Y_{se})\cdot U_{sa} - \underbrace{U_{ss}}_{<0}U_{ea}\right). \tag{10}$$

Besides the SE and IE, the effect on study time and learning intensity is driven by the interrelatedness of both which is captured by Y_{se}. Suppose that high-ability students choose to increase study time (relative to a low-ability student). If both effort dimensions were complements, high-ability students would, ceteris paribus, also learn with higher intensity. If, in contrast, s and e were substitutes, increased study time would, ceteris paribus, come at a price of lower learning intensity. Given the general formulation of the EPF, the relationship between the two effort dimensions is unclear. As such, the effect on s^* and e^* is in general ambiguous.

2.3.2. Job market prospects

Suppose now that labor market prospects of the student improve, i.e. δ increases. We abstain from analyzing the effect on $\bar{s}$ and $\bar{e}$ and immediately compute the implications for s^* and e^*. Totally differentiating (5) and (6) implies:

$$\frac{ds^*}{d\delta} = \frac{1}{\underbrace{|H|}_{>0}}\left(U_{se}(Y_{se})\cdot U_{e\delta} - \underbrace{U_{ee}}_{<0}U_{s\delta}\right), \tag{11}$$

$$\frac{de^*}{d\delta} = \frac{1}{\underbrace{|H|}_{>0}}\left(U_{se}(Y_{se})\cdot U_{s\delta} - \underbrace{U_{ss}}_{<0}U_{e\delta}\right), \tag{12}$$

with $U_{s\delta} = \beta Y_s\left(V_{I^2I^2}Y\delta + V_{I^2}\right)$ and $U_{e\delta} = \beta Y_e\left(V_{I^2I^2}Y\delta + V_{I^2}\right)$.

This shows that the impact of improved labor market prospects on student's behavior depends also on a.) the interplay of SE and IE and b.) the interrelatedness of study time and learning intensity. The intuition is analog to the one described in the previous subsection. As a result, the consequences for s^* and e^* are in general ambiguous.

2.4. Predictions

To gain testable predictions, we have to choose an explicit formulation of the sub-utility function V and of the EPF Y. With respect to the former, we assume that the utility of income and leisure is described by a Cobb-Douglas function $V = I^{\alpha}L^{1-\alpha}$ with $0 < \alpha < 1$ (for a similar assumption see e.g. Mankiw, 1988). Regarding the latter, we follow the literature and assume that the EPF is given by $Y = e^{\gamma_1}s^{\gamma_2}a^{\omega}$, $0 < \gamma_1$, $\gamma_2 < 1$ and $\omega > 0$, which is also a Cobb-Douglas type function.[10]

These assumptions have two important implications. First, the SE will always dominate the IE, i.e. $U_{sa} > 0$, $U_{ea} > 0$, $U_{s\delta} > 0$ and $U_{e\delta} > 0$. Second, study time and learning intensity are complements, i.e. $Y_{se} > 0$. It is simple to show that $U_{se}(Y_{se}) > 0$ holds, too. Using (9), (10), (11) and (12), we then find:

[8] The second-order conditions for a maximum are given by $U_{ss} < 0$, $U_{ee} < 0$ and $|H| = U_{ss}U_{ee} - U_{se}U_{se} > 0$, where $|H|$ is the determinant of the Hesse-matrix. We assume that these conditions are fulfilled.

[9] Since the student's ability is constant by definition, the results of the comparative static exercise should be interpreted as predictions of how individuals with different abilities, but otherwise identical characteristics, behave during academic studies.

[10] Formalizing the EPF as a Cobb-Douglas function is a widely used assumption in the literature. See, for instance, Gyimah-Brempong and Gyapong (1991); Polachek, Kniesner, and Harwood (1978) and Bishop and Wößmann (2004).

Prediction 1. High-ability students choose a higher study time (lower leisure) and provide more learning intensity compared to low-ability students.

Prediction 2. An improvement of labor market prospects raises study time and learning intensity.

Because of our general framework, different assumptions on the functional form of V and Y would lead to different predictions. If, for instance, IE dominated SE, high-ability students would choose less effort and an improvement of labor market prospects would decrease effort. Therefore, the effects of both on study time and learning intensity remain an empirical question.

3. Empirical investigation

3.1. Data

3.1.1. The NEPS

To test our theoretical predictions empirically, we exploit data from the National Educational Panel Study (NEPS). The NEPS includes more than 200 institutions of higher education in Germany, which allows for analyses based on a representative nation-wide sample. To the best of our knowledge, we are the first to use this dataset to investigate the determinants of student effort. The NEPS carries data of several cohorts covering the life span of individuals from early childhood up to further education and lifelong learning. We utilize the starting cohort 5, which provides representative data on freshman students starting in winter term 2010/2011.[11]

From the perspective of our research aims, focusing on study beginners is advantageous due to the students not being affected by their own study success. Additionally, we take the issue of potentially selective dropouts into account. Study dropouts are an ongoing problem not only in Germany but also in many other countries (see Di Pietro & Cutillo, 2008; Light & Strayer, 2000). In recent years, only three quarters of students completed their studies at German universities (OECD, 2013).[12]

3.1.2. Variables

Our focus lies on the variables covering students' efforts. For the quantity of effort, we analyze time use data. The NEPS offers detailed information on the average time allocation of each individual's daily activities (see Appendix A.1 for more information on question wording and variable definition). Specifically, students are asked about their time spent on self-study, lecture attendance, other study-oriented activities (e.g. commuting), working, household activities and childcare. Following the findings of Bratti and Staffolani (2013), we expect self-study to be the key quantitative effort variable, but we also examine the role of lecture attendance.[13] The NEPS also provides information on study time during semester breaks, which adds to time use during the semester.

As in other empirical settings using data on university students (see e.g. Bonesrønning & Opstad, 2015), there is no exact measure of the qualitative dimension of student effort in the NEPS data. Yet, by means of a subjective assessment on individual effort levels, we are confident that we capture differences in individual effort apart from the amount of time spent on studying. Hence, as a proxy variable for the qualitative dimension of effort, we use information on how strongly each student agrees to the statement "I invest a lot of energy in being successful in my studies." Possible answers reach from "Does not apply" (1) to "Applies completely" (5) on a five-point scale. About two thirds of the students state values (3) and (4), while only a few report to invest very little or the maximum amount of energy. We refer to this variable as "self-assessed effort" in the following. Figure B.1 in the online appendix visualizes the distribution of this variable as well as the effort indicator based on self-study time using histograms. For both of our key effort variables, we also show separate histograms across genders.

We exploit data collected by the NEPS to develop a rather unique measure of ability. While many social sciences discuss the concept of ability in general and the role of ability tests in particular (see e.g. Nash, 2001), we benefit from several advantages of the NEPS data. First, in contrast to other data sources in educational research, the survey designers paid particular attention to measuring individual ability levels of each student, and conducted expensive and comprehensive competency tests. In spring of 2011, thousands of students participated for a reward of 20 Euros in voluntary tests organized at the universities. Second, this payment was unconditional on test outcomes to avoid having an economic incentive manipulate the test results. Third, the actual contents of the tests were not announced in advance, which further eliminates the possible influence of test preparation. Thus, even if students had an incentive to manipulate the outcomes of the test by putting in additional efforts, this would have hardly been possible. Arguably, in the education context, most proxies of ability are affected by individual effort levels, preventing a clean identification of actual ability.[14] The three parts of the test include reading speed, reading competency and mathematical tests, which relies on the idea that reading and mathematical skills cover most of the required core competencies of present students. Being able to conduct quantitative analyses has become increasingly important in most sciences, while an ambitious workload of reading is part of nearly every field of study. We standardize the variables of each test with a mean of zero and a standard deviation of one to generate a comprehensive variable of all three competency tests.[15]

[11] Other starting cohorts focus on early childhood (cohort 1), kindergarten (cohort 2), lower secondary school (cohort 3), upper secondary school (cohort 4), and adults who are out of the education system (cohort 6). The data of the fifth one (doi:10.5157/NEPS:SC5:6.0.0) was collected by the NEPS via telephone and online. Note that from 2008 to 2013, NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide network. For further information see Blossfeld, Roßbach, and von Maurice (2011).

[12] During the time when the NEPS fieldwork commenced, some of the federal states required university students to pay tuition fees. Typically, there are no tuition fees at Germany's mainly tax-payer funded universities. This was different in the winter term of 2010/2011 in the federal states of Hamburg, Lower Saxony, North Rhine-Westphalia, Baden-Wrttemberg and Bavaria. Those states introduced tuition fees in the years 2006 and 2007, but the size of the tuition paid by university students was relatively small, compared to countries like the UK. Still, federal state governments decided to abolish the unpopular fees over the last years. In additional analyses, we conduct robustness checks for our main findings by including a variable for the existence of tuition fees during the period of data collection. The results are robust and are available upon request, just like all other results that we mention but do not present.

[13] Especially in the German context, there are certainly differences in the nature of these two activities, self-study and course attendance. Students may well attend classes but they are usually not required to pay attention to the lecturer or to take an active part in course lessons. It is thus quite common at German universities that some students do not attend lectures but still take the exam at the end of the semester after intense self-study and exam preparation.

[14] A correlation analysis shows a positive relationship between high school grades and student effort. High school grades are also strongly related with our ability indicator, as better grades at high school generally go along with better competence scores. Yet, there is remaining variation in the competence test scores that cannot be explained by grades. As our ability indicator is also related to grades at university, the competence scores appear to be a reliable predictor of student performance.

[15] Due to the voluntary nature of participation in the test, data on ability is not provided for all participants of the NEPS surveys, which leads to a reduced sample size in the first part of our analysis. In turn, we can increase observation numbers in the second part of the analysis by focusing on a survey-based determinant of effort, while we make use of NEPS weights to foster representativeness of the data throughout our analyses.

Table 1
Ability and (qualitative) student effort.

	(1) Self-assessed effort	(2) Self-assessed effort	(3) Self-assessed effort	(4) Self-assessed effort
Ability	−0.075***	−0.056**	−0.053**	−0.085***
	(0.02)	(0.02)	(0.02)	(0.02)
Socio-demogr. controls		✓	✓	✓
School history/ life circumstances			✓	✓
Work-/university-related controls				✓
Observations	4431	4431	4431	4431
Adj. R^2	0.005	0.019	0.023	0.046

OLS estimations; NEPS weights used; robust standard errors in parentheses $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Additional dummy variables for the interview month are included in columns (2)-(4). Full results are reported in table B.1 in the online appendix. Note that the online appendix also contains extensive regression tables for the other analyses shown in the main part of the paper.

To inspect the role of students' future employment outlooks as a potential driver of differences in effort decisions, we exploit information on job market prospects. Part of the NEPS questionnaire is the following question: "And once you do complete the degree course, what are your chances of getting a good job?" Five answers are possible, which reach from "very bad" (1) to "very good" (5). Only very few respondents (about 4%) state very bad or bad prospects (value 1 or 2), while about 46% have good prospects and about 30% of the sample have very good prospects. We build a dummy variable, which equals one if prospects are very good (5). Besides data on subjective job prospects, our dataset provides further information on students' prospective jobs. This allows us to analyze the impact of job prospects in greater depth, as we merge the NEPS data with labor market data, differentiating them by occupation and region. As job market prospects are not necessarily exogenous, we include official unemployment statistics from the Federal Employment Agency for an instrumental variable (IV) approach, which we describe in more detail later on.

The NEPS offers a large amount of data on students in Germany's system of higher education, which allows us to consider several control variables on important aspects of students' lives. As illustrated in Table A.1 in the appendix, we categorize the relevant information into socio-demographic background, life circumstances, school history and university background as well as economic factors, with the latter category also including regional information. As part of the variables reflecting the factors of interest at university, we consider a subjective variable on the enjoyment of studying, which allows us to capture differences with respect to intrinsic motivation. We also consider possible measurement differences over time by using control variables for interview month throughout our analysis. We only restrict the sample by excluding outliers in regard of age (students above 40 years). Consideration of non-responses (i.e. missing values) to all the relevant survey items that we take into account leads to a sample that includes more than 4400 students who have completed all parts of the competency test. Table A.1 shows the descriptive statistics of the variables used.

To illustrate the available information on study-related time (i.e. self-study, attending classes and further study-oriented activities) and other activities, such as working, Fig. A.1 in the appendix shows the distribution of students' time use during the semester. The remaining share of time not reflected in one of the survey items offers us another variable of interest for our analyses. To that end, we calculate students' free-time (including weekends and sleep) by adding all hours up and deducting that number from the weekly stock of $(24 \times 7 =)$ 168 h. This leisure indicator allows us to consider the fact that some students have less time for studying than others, not because of laziness, but because of having a job, for example.

3.2. Student effort and ability

3.2.1. Main results

To investigate the role of ability for student effort decisions, we exploit our continuous measure and first inspect its basic relationship to self-assessed effort levels. We run standard regression analyses and consider relevant control variables to inspect whether the basic difference between high- and low-ability types in regards to their self-assessed effort levels is sensitive to some key characteristics. In a second step, we focus on the quantitative dimension of effort and examine various time-use variables as outcomes.

The main finding of Table 1 is a significant and negative effect of ability on self-assessed effort that does not change much throughout the specifications. Column 2 adds socio-demographic controls while column 3 additionally controls for life circumstances and school history. The effect remains strong when we consider all variables together, including university- and work-related variables in column 4.

As our outcome variable here may reflect not only the qualitative dimension of effort, as in our model, but also the quantitative dimension, we inspect the consequences of controlling for the latter using time-use data. The finding of a negative ability effect holds, which is further evidence contrary to our prediction. Other sensitivity analyses confirm our main finding. In fact, while we prefer standard regression analyses in this part of the empirical investigation, we can also estimate an ordered probit model to take the ordinal scale of our dependent variable into account. Again, we reach the same conclusion, independent of whether we look at ability as a continuous variable or whether we use dummy variables for different quantiles of ability. In regard to sample selection, we estimate a Heckman model in order to check whether the results are subject to a selection bias caused by the voluntary participation in the competency test but no evidence points towards such type of selectivity.[16] In further robustness checks, we exclude students with a foreign mother tongue who might have a disadvantage in the reading tests. To fully rule out that the findings are related to interview timing, we replace the control variables for interview month with more detailed information for the exact week of the interview. We also re-run specification 4 excluding the control variable

[16] To employ an instrument, we can make use of information on interviewer contact attempts. This indicator reflects the interviewer effort needed to reach targeted students. Basically, the more interviewer contact attempts are necessary, the less likely the student is a test participant. While this fact allows for having a relevant instrument on the first stage of the two-step estimator, we have to assume that interviewer contacts are unrelated to subjectively assessed student effort.

Table 2
Ability and (quantitative) student effort.

	(1) log(Self-study (term))	(2) log(Self-study (holidays))	(3) log(Attend classes)	(4) log(Free-time)
Ability	−0.034* (0.01)	−0.090*** (0.03)	0.011 (0.01)	0.011^{+} (0.01)
Observations	4431	4431	4431	4431
Adj. R^2	0.052	0.065	0.047	0.059

OLS estimations; NEPS weights used; robust standard errors in parentheses $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of control variables is used in each column, as in column (4) of Table 1. Additional dummy variables for the interview month are included in each column. Full results are reported in table B.2 in the online appendix.

for enjoyment of studying, which could be considered as potentially endogenous. Finally, the rich data allows adding further control variables for school history, such as the subjects chosen by students for their school-exit-examinations, which does not change our finding either.

Next, we focus on the effect of ability on quantitative study efforts. Table 2 shows our findings for several potential indicators, for which we use the log of each time-use variable. As our main outcome variable of interest, we first find a negative effect of ability on self-study time. The finding is the same, although with an even stronger effect size for the self-study time between terms. Arguably, this quantitative effort indicator could be even more telling, taking into consideration that, during the holidays, students manage their time completely autonomously, deciding whether or not to put in extra effort for university. Using lecture attendance as a dependent variable in column 3, the estimation shows a slightly positive but statistically insignificant impact of ability. This is in line with the expectation that attendance does not reflect effort levels in the way that self-study does. Given the background of the German system of higher education with its focus on intense exam preparation at the end of the semester, one could interpret the results as many students attending classes for other reasons than improving academic achievement, such as socializing.[17] Finally, we regress our generated variable of students' free-time on ability. The result in column 4 shows that ability has a contrary effect in the sense that having higher ability implies enjoying more free-time if we accept a significance level of 10%. While this illustrates the main finding of our empirical investigation really well, the free-time measure certainly is somewhat noisy, as it indirectly considers the heterogeneity in students' lives and the fact that some students are influenced by factors such as work or children in addition to studying. Overall, however, we conclude from our additional sensitivity analyses that the main finding of leisure-enjoying high-ability types holds, which stands in contrast to our theoretical prediction.

3.2.2. Discussion

Our results reject the expectation of stronger efforts among high-ability compared to low-ability types of students. Rather it seems that a lazy genius phenomenon exists of students with great prospects in their lives who put in relatively little effort during their studies. Apart from these interpretations, however, other aspects could (possibly) influence our empirical analysis. One of the concerns is linked to the understanding of ability as an exogenous factor that is unaffected by effort. While we argue that our ability measure based on competence testing is less affected by past learning efforts than alternative proxies, such as high school grades, these test results are still not immune to past choices on effort. Having said that, one could also suspect that those past efforts are related to current efforts, in consequence of which the empirical link between ability and effort could be biased upwards. As illustrated above, we consider the role of study effort in our ability measure to be negligible, given a clear lack of opportunity and incentives for any preparation of the test. Most importantly, such a potential bias cannot explain the result of a negative relationship between our ability measure and effort. If anything, our finding is even more striking, as we would underestimate the negative effect of ability on effort.

Another possible concern regarding the empirical procedure relates to our idea of analyzing effort based on subjective self-assessments, which might be susceptible to measurement issues. Concretely, the research on subjective data considers the possibility of a reference bias in self-reports (Groot, 2000). One could argue that high-ability students generally report lower effort levels, as their reference point is different. During the course of their studies, they cultivate different social contacts at the university and compare themselves to other students with high abilities rather than to those with low abilities. Yet, several aspects speak against such type of measurement problem.

First, we rely on data from the outset of the individuals' studies. In this phase, the freshmen are not segregated according to their ability yet, which reduces the likelihood of peer effects in self-reporting within their subjects.[18] Second, if peer effects led to reduced self-assessed effort levels, while the effort levels of the high-ability types were actually higher than those of the low-able, one would expect a narrowing of the gap between the two groups, not a complete reversal. Third, any effect of ability on self-reports is hampered by the fact that students are not necessarily fully informed about their actual ability levels.[19] Fourth, the fact that we observe a fairly similar picture in both, self-assessed effort and the amount of time students spend on self-studying, conforms to our interpretation. In the case of the latter, we again observe that high-ability students report putting less effort into their studies in regard to the key factor self-study time, which is a variable that is arguably more objective. Fifth, while reference bias is seen as a relevant issue in the analysis of life satisfaction (see Odermatt & Stutzer, 2019), as happy people may have different standards of a happy life, we are not aware of any evidence supporting a similar idea for self-reported effort. If anything, individuals could possibly have a desire to over-report efforts due to image concerns (Ewers & Zimmermann, 2015), which could be a particular issue for individuals with high standards. If one is willing to assume that such

[17] In additional analyses, we examine the link between the different time-use variables and academic success, measured in grades and study progress. While self-study is significantly related to our indicators of study success, lecture attendance seems to play no role.

[18] A relevant phenomenon in this context is the orientation week at German schools of higher education where the freshmen get into social groups through a randomization procedure (Girard, Hett, & Schunk, 2015). For the first year or even longer, students typically stay together during lectures, when learning and in their non-university life. In consequence, not only work willingness but also the ability levels of their 'random' friends are typically very heterogeneous for German students, at least in the outset of their studies.

[19] See Gary-Bobo and Trannoy (2008) for a discussion of students with imperfect knowledge of their ability. Also see Stinebrickner and Stinebrickner (2014) who provide empirical evidence on how students misperceive their ability to perform well.

Table 3
Job market prospects and student effort.

	(1) Self-assessed effort	(2) Self-assessed effort	(3) log(Self-study (term))	(4) log(Self-study (term))
Very good job prospects	0.189***	0.136***	0.120***	0.099***
	(0.04)	(0.03)	(0.03)	(0.02)
Ability	−0.088***		−0.036*	
	(0.02)		(0.01)	
Observations	4409	10233	4409	10233
Adj. R^2	0.052	0.046	0.058	0.051

OLS estimations; NEPS weights used; robust standard errors in parentheses $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of control variables is used in each column. Additional dummy variables for the interview month are included in each column. Full results are reported in table B.3 in the online appendix.

form of approval-seeking in self-reported effort is more likely among high-ability types in high-ability environments, this again would imply that we underestimate our result regarding the lazy genius. Lastly, we can check the role of varying contexts regarding high- vs low-ability peers empirically by considering differences across fields of study. While additional inspections of the data do not reveal any striking differences in variation of ability or effort across subjects, we are still cautious in considering subjects directly in our analysis, since endogenous self-selection related to our variable of interest could occur. Instead, we prefer using an alternative effort indicator as dependent variable for assessing the role of subject heterogeneity in our analysis. To do so, we define an adjusted effort variable as the individual deviation from the average effort in each field of study according to the available 2 digit ISCED classification.[20] While this alternative outcome variable considers differences in effort across subjects, the analysis of this subject-adjusted effort leads to the same finding regarding the negative impact of ability on effort. The results are shown in Table A.2 in the appendix and rather indicate that the effects become stronger when we consider subject differences. As a further check, we re-run our analysis for subsamples based on subjects but again do not find any evidence for positive effects of ability on effort. We conclude from these considerations that the empirical findings are valid and do not result from giving special attention to subjective data in our investigation.

3.3. *Student effort and job market prospects*

3.3.1. *Main results*

To empirically test our second theoretical prediction, we begin with standard regressions in the vein of the previous chapter. The determinant of student effort in this case is their job market prospects, for which we analyze subjective self-assessments. We include a dummy variable that distinguishes between students with excellent job market prospects and those who do not report such a positive outlook. For a comparison, we show estimation results based on the small sample used so far, which includes ability. We then show results based on a sample with more than 10,000 individuals, which we can use by not considering ability.

The main finding of Table 3 is that subjective job prospects are positively linked to both effort dimensions, i.e. self-study time during term (columns 1 and 2) and self-assessed effort levels (columns 3 and 4), irrespective of the sample that we use. In contrast to our analysis of the impact of students' ability levels, this is in line with our theoretical considerations. However, while there is no reason to believe that students' current effort levels vice versa affect their ability levels (negatively), the potential problem of reverse causality is certainly an issue here. One may argue that it is not the great prospects that spur effort but that great prospects result from high effort levels.

To check the direction of the effect of perceived job market prospects on effort levels, we employ an IV approach for which we exploit labor market data. The idea is that variation in labor market conditions in the region where the university is located is a) effectively influencing perceptions of one's own future employment outlook and b) plausibly determined exogenously and thus not dependent on effort decisions of students at the university.[21] Current variations in local labor market conditions may not influence a student's actual employment situation in the future, but we expect an impact on his or her perception of it. Specifically, we focus on labor market dynamics by using data on the amount of newly unemployed persons, i.e. changes in regional labor market conditions, which occur after the start of our investigation period. This is important, as given local unemployment rates may be related to institutional quality or other relevant regional characteristics, while, arguably, the dynamic changes in labor market conditions are not. To implement our idea, we identify the relevant labor market segment of each student by exploiting available information on the most common career aspiration for each field of study in the NEPS data. These career aspirations are measured on a standard classification of occupations (KldB1988), which allows us to merge the NEPS data with employment statistics from Germany's Federal Employment Agency at the industry level. As these industry-specific statistics are available at the regional level (German federal states), we can merge the employment statistics with our NEPS data based on the occupation identifier and the federal state where the university is located. This procedure yields a large number of cells (= industry × state), for which we can attach information on varying labor market conditions to the NEPS data. As our IV, we use actual numbers of additional unemployed persons within each regional industry sector divided by overall employment numbers per cell. This weighted inflow from employment to unemployment varies between 0 and 20 percentage points with a mean of 1.3 and a median of 0.8 percentage points. In a last step, we multiply this inflow variable with 100 and take the square root to consider outliers. As an exogenous and unanticipated influence during their studies, we expect our instrument 'unemployment inflow' to decrease students' perceived job prospects after enrollment. Since most students were interviewed at the end of the first term and our particular interest lies in job prospects during the term, we use data on unemployment entries from October to December 2010 and relate those to employment data of the same labor market segment from September 2010. Additional robustness checks show that our results do not depend on choosing those time points.

In terms of methodology, we prefer a procedure proposed by

[20] The 2 digit ISCED 1997 classification distinguishes between 21 fields of study (ranging from "Teacher training and education science" to "Environmental protection") and was promulgated by UNESCO in 1997.

[21] For a similar IV approach using regional labor market data from Germany, see Reichert, Augurzky, and Tauchmann (2015).

Table 4
Job market prospects and student effort (IV estimations).

	(1) Very good job prospects	(2) Self-assessed effort	(3) log(Self-study (term))
Unemployment inflow	−0.628***		
	(0.05)		
Very good job prospects		0.606***	0.351***
		(0.13)	(0.09)
Observations	10233	10233	10233

IV-2SLS Wooldridge procedure estimations. Probit estimations in column (1), second stage (IV) estimations in columns (2) and (3); NEPS weights used; robust standard errors in parentheses $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of control variables is used in each column. Additional dummy variables for the interview month are included in each column. Full results are reported in table B.4 in the online appendix.

Wooldridge (2002) for potentially endogenous binary variables over the standard linear probability model. Hence, in a first step, we estimate a probit model for very good job prospects using unemployment inflow as independent variable. In a second step, we include the predicted values as an instrument in standard two-stage least-squares regressions. Employing this procedure, statistical significance tests yield asymptotically valid results (Wooldridge, 2002).

The IV results in Table 4 substantiate the idea that job market prospects have a positive effect on effort levels. This holds for both of our effort variables, the subjective assessment and the key time-use variable of self-study. As shown in column 1, the probit estimation confirms our expectations regarding the impact of our instrument on job prospects. The instrument has the expected sign and is statistically significant. Thanks to the exogenous nature of changes in regional labor conditions, we interpret the second-stage results presented in columns 2 and 3 as evidence for a direct impact of students' employment outlook on their behavior.

3.3.2. *Discussion*

In this subsection, we briefly discuss our main findings regarding the role of job market prospects in student effort, starting with a report on a few robustness checks. Our findings are qualitatively similar when running a standard linear IV model with clustering of standard errors at the cell level (results are shown in Table A.3 in the appendix). The first stage regressions again show that our instrumental variable has a strong effect on job market expectations, which ensures sufficient instrumental power (the F statistic is 34.66). Given the ordinal nature of one of our two effort variables, we conduct another sensitivity check for self-assessed effort and confirm the finding of a significantly positive impact of great employment prospects by using bivariate ordered probit (see Sajaia, 2008).

In further checks, we repeat the analysis by using different definitions of the instrument. For instance, we apply the logarithm instead of square root to determine the IV, and we create an alternative instrument by exploiting changes in unemployment rates over time. Furthermore, we conduct robustness checks by restricting the sample in different ways. For instance, we exclude students from our sample who reported having earned 60 credit points or more, which may conflict with their assumed freshman status. We can further exploit the information on interview dates by excluding observations from students who were interviewed late during the NEPS fieldwork. These modifications do not change our results in a qualitative way.

When comparing OLS results from the analysis at the beginning of the section with our IV results, we observe larger effect sizes when making use of an instrumental approach. This suggests that the former underestimate the importance of job market prospects in student effort and that the actual effect is stronger when considering endogeneity. This might be explained by heterogeneity in responses to the question on job prospects. Some highly motivated students may be less concerned about their individual future than others, and they thus may underreport their prospects despite actually having very good job market perspectives.

3.4. *Effect heterogeneity*

The main results from the previous sections indicate that students with the perception of a great job market outlook do not lean back like high-ability types do, but instead provide high effort levels. To better understand these results, it is helpful to find out which groups of students drive our findings about the role of ability and job prospects in student effort. We suspect the group of male students to explain lacking efforts, given the gender gap in educational outcomes (Goldin, Katz, & Kuziemko, 2006). Note that we observe gender differences in effort throughout our analyses (see figure B.1 as well as tables B.1 to B.4 in the online appendix). A second group of interest in our context studies STEM (Science, technology, engineering, and mathematics) subjects.[22] In these fields, job prospects are typically believed to be excellent for German students, so that the current labor market development may not hold significance for them.

To learn more about effect heterogeneity, we expand our analysis by considering interaction terms in regression models. We inspect subgroup differences in the effects of ability and job market prospects. Regarding the latter, we use the instrument of unemployment inflow in a reduced-form fashion to allow for a consistent interaction analysis. Since we investigate effect heterogeneity in joint specifications, we use the smaller sample of students who participated in the competency tests.

Regarding ability, the results in Table 5 show significant negative effects in student effort across both genders (columns 1 and 2). The interaction term is not significant, though the effect appears to be somewhat stronger for males. However, adding the coefficients for ability and the interaction (female × ability) yields a significant effect for females only with respect to subjectively assessed effort, not for time spent on self-study. This suggests that in particular high-ability males provide lower efforts than their low-ability counterparts by putting in less time for studying. Given that STEM subjects are selected more often by male students than by female students, it comes as no surprise that we yield similar findings for STEM students (columns 3 and 4). A weakly significant interaction term in column 4 (STEM × ability) indicates that the negative ability effect in effort is driven by students of STEM subjects.

Regarding job market prospects, Table 5 reveals significant subgroup differences for STEM and non-STEM students in the effects of unemployment inflow (columns 3 and 4). In fact, adding up the effects yields the result that STEM students are not affected at all by unemployment inflows. While there are no gender differences in the

[22] We use the 2 digit ISCED classification to make the distinction between STEM and non-STEM subjects. Accordingly, STEM subjects are life science, physical science, mathematics and statistics, computing, and engineering.

Table 5
Analysis of effect heterogeneity using interaction variables.

	(1) Self-assessed effort	(2) log(Self-study (term))	(3) Self-assessed effort	(4) log(Self-study (term))
Ability	−0.111***	−0.055*	−0.084***	−0.027
	(0.03)	(0.02)	(0.02)	(0.02)
Unemployment inflow	−0.165**	−0.082+	−0.186***	−0.072**
	(0.06)	(0.05)	(0.03)	(0.03)
Female	0.219**	0.094	0.245***	0.143***
	(0.08)	(0.06)	(0.04)	(0.03)
Female × Ability	0.039	0.034		
	(0.04)	(0.03)		
Female × Unemployment inflow	−0.005	0.012		
	(0.07)	(0.05)		
STEM			−0.172	−0.001
			(0.11)	(0.07)
STEM × Ability			−0.033	−0.049+
			(0.04)	(0.03)
STEM × Unemployment inflow			0.294**	0.151*
			(0.10)	(0.07)
Observations	4371	4371	4371	4371
Adj. R^2	0.052	0.056	0.056	0.065

OLS estimations; NEPS weights used; robust standard errors in parentheses $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of control variables is used in each column. Additional dummy variables for the interview month are included in each column.

effects of job prospects on students effort (columns 1 and 2), it is clear that non-STEM students drive our findings in Section 3.3. Possibly, concerns about labor market developments are more important for those students than for STEM students. The latter may feel confident about their own future career independent of current developments and do not adjust effort levels. Given that STEM students with high ability are providing relatively low effort levels, we conclude that even worsening labor market conditions are not capable of triggering higher efforts among those talented individuals.

4. Conclusion

The aim of our paper is to improve the understanding of students' decision-making concerning their willingness to provide effort. We build a simple model and show that both students' abilities and job market prospects are predicted to increase effort. Our empirical findings on the impact of labor market prospects on student behavior are in line with this prediction. Accordingly, having a positive outlook on future earnings positively influences current effort levels. From a policy perspective, this appears to be a convenient finding, even if happiness researchers are correct in arguing that individuals to some extent overestimate the utility of future income (see e.g. Easterlin, 2001; Frey, Benesch, & Stutzer, 2007). However, this finding implies, vice versa, that bad labor market prospects could reduce effort levels at universities. Our evidence thus conforms to the conclusions of other researchers, such as Aina et al. (2011), who consider weak job prospects as an explanation for long study durations at Italian universities. In a similar fashion, van der Klaauw and van Vuuren (2010) argue that low labor market returns to academic performance explain the phenomenon of lacking ambition among Dutch students. It appears that we can provide empirical support for the important role of the labor market in student behavior for another country.[23]

The empirical evidence on the role of ability in student effort decisions is, however, in contrast with our prediction. Nevertheless, we can use the general form of our model to explain the finding of the 'lazy genius'. Since both effort dimensions decline in ability, we can conclude that study time and learning intensity are complements. The theoretical reasoning then suggests that the IE (SE) of high-ability students is relatively strong (weak) compared to that of low-ability students.[24] This could be because the future marginal utility gain of putting in high effort is relatively low for high-ability students since their abilities per se ensure a high level of educational achievement and thus a high level of expected income after studying. It is then rational for those students to reduce efforts as this is associated with a marginal utility gain during academic studies (e.g. students can increase leisure), which does not come at the expense of a high reduction of future utility gains. As a result, the assumed Cobb–Douglas specification of the EPF seems appropriate when we empirically investigate the relationship between job market prospects and effort but fails with respect to the 'lazy genius'.

Besides this interpretation, it might also be the case that some assumptions of the model fail. For example, it could be simply false that individuals benefit from raising their future income levels. One may question previous studies in favor of the human-capital theory and instead argue that higher education is in itself not necessarily relevant for one's potential to perform well in the labor market.[25] However, from the individual student's perspective, even if there were no human capital effect for income levels, educational achievement should work as a signal to potential employers. In this context, Arcidiacono, Bayer, and Hizmo (2010) argue that graduation helps reveal ability to the labor market and thereby affect earnings, according to which high-ability students benefit in particular from successful studying. This leads to the question whether students believe in the importance of such a signal or whether they doubt that their degrees are key to labor market success in the future. Phenomena like grade inflation could be relevant in explaining why students are reluctant with their effort if they expect that the informative power of their educational success is not very effective.[26]

[23] Also see Kahn (2010) who provides empirical evidence for the US on how bad labor market conditions during graduation negatively affect students' labor market outcomes later on.

[24] For related discussions, see Card (1995) and Bandiera et al. (2015).

[25] See e.g. Bedard (2001) and Frazis (2002) for more skeptical views on the human capital argument.

[26] For discussions on the informative value of grades, see e.g. Grant (2007) as well as Chadi and de Pinto (2018).

Note, however, that schools of higher education have particular interest in avoiding the reduction of their degrees' value, as pointed out by Ehlers and Schwager (2016). Hence, the finding of little effort among high-ability types remains intriguing, especially since we find that students with better job market prospects are indeed motivated to put greater efforts into studying.

Appendix A

A1. Variable definition of time use variables

English questionnaire: "How many hours in a typical week during term time do you spend doing the following activities?"

- Attend classes (lectures, seminars, tutorials, internships, etc.)
- Self-study (e.g. preparing, reviewing for class, preparing presentations, specialist reading, revision courses, student learning groups, homework, papers, exam preparation)
- Other study-oriented activities (e.g. library work, office hours, travel time)
- Employment
- Household (cleaning, shopping, etc.)
- Child care

Additional information for each item: "Please enter a figure for each activity, rounded to the full hour. Mark 'no time expenditure/not applicable' if you do not spend any time doing that activity or the activity does not apply to you."

Variable definition: If the activity is not applicable, we replace the value of the respective variable by zero. This affects only a few cases (with the exception of child care, which is not applicable for most students). In order to consider outliers, we use logarithmic values of each time use variable. Observations with a zero are manually set to zero after taking the logarithm.

A2. Tables and figures

Table A.1
Descriptive statistics.

	Mean	Sd	Min	Max
Dependent variables and further time use data				
Self-assessed effort	3.584	1.010	1.0	5.0
Time: Self-study (term)	13.261	9.225	0.0	90.0
Time: Self-study (holi.)	12.420	14.859	0.0	99.0
Time: Attending	22.884	7.045	0.0	60.0
Time: Study-oriented	5.139	4.231	0.0	90.0
Time: Job	3.807	5.650	0.0	45.0
Time: Household	4.544	3.453	0.0	35.0
Time: Childcare	0.352	3.754	0.0	99.0
Socio-demographics				
Female	0.557	0.497	0.0	1.0
Age	21.519	2.290	18.0	38.9
Migration	0.076	0.266	0.0	1.0
Foreign citizenship	0.024	0.152	0.0	1.0
Foreign mother tongue	0.055	0.228	0.0	1.0
School years (father)	14.808	2.532	9.0	18.0
School years (mother)	14.370	2.434	9.0	18.0
No partner	0.451	0.498	0.0	1.0
Partner, living apart	0.421	0.494	0.0	1.0
Partner, living together	0.129	0.335	0.0	1.0
Life circumstances and school history				
Children in household	0.010	0.101	0.0	1.0
Single person household	0.281	0.449	0.0	1.0
Living with parents	0.238	0.426	0.0	1.0
Living in dorm	0.132	0.339	0.0	1.0
Living in rented flat	0.587	0.492	0.0	1.0
Living in own flat	0.010	0.102	0.0	1.0
Living in a sublet	0.033	0.179	0.0	1.0
Repeated high school year	0.112	0.315	0.0	1.0
Gymnasium	0.771	0.420	0.0	1.0
Nontraditional A levels	0.020	0.141	0.0	1.0
University and work related controls				
U of Applied Science	0.331	0.471	0.0	1.0
Teaching track	0.104	0.305	0.0	1.0
Change of subject	0.076	0.264	0.0	1.0
Enjoyment of studying	4.387	0.726	1.0	5.0
Region: North	0.133	0.340	0.0	1.0
Region: West	0.187	0.390	0.0	1.0
Region: South	0.402	0.490	0.0	1.0

(*continued on next page*)

Table A.1 (*continued*)

	Mean	Sd	Min	Max
Region: East	0.277	0.448	0.0	1.0
Working	0.478	0.500	0.0	1.0
Income	898.305	677.609	0.0	10870.0
Funding: Family	0.743	0.437	0.0	1.0
Funding: BAföG*	0.332	0.471	0.0	1.0
Funding: Bank loan	0.031	0.174	0.0	1.0
Funding: Earnings	0.564	0.496	0.0	1.0
Funding: Apprentice pay	0.050	0.218	0.0	1.0
Funding: Own resources	0.250	0.433	0.0	1.0
Funding: Gov. benefits	0.312	0.463	0.0	1.0
Funding: Scholarship	0.058	0.233	0.0	1.0
Funding: Other	0.014	0.117	0.0	1.0
Funding: Third parties	0.650	0.477	0.0	1.0
Variables of interest				
Job prospects**	4.081	0.799	1.0	5.0
Ability	0.000	1.000	-4.9	4.0
Observations	4431			

NEPS weights used.
* BAföG is the abbreviation for the Federal Training Assistance Act, which regulates grants and loans for students in Germany.
** Number of observations for job prospects is 4409 and is slightly lower than for the sample shown here (due to 22 missing values).

Table A.2
Study effort and ability using deviation from the mean.

	(1) Adjusted self-assessed effort	(2) Adjusted self-study time (term)	(3) Adjusted self-study time (holidays)	(4) Adjusted time for attending classes	(5) Adjusted free-time
Ability	−0.095***	−0.648***	−1.216***	−0.058	0.619⁺
	(0.02)	(0.19)	(0.29)	(0.14)	(0.35)
Observations	4431	4431	4431	4431	4431
Adj. R^2	0.048	0.024	0.055	0.056	0.081

OLS estimations; NEPS weights used; robust standard errors in parentheses $^+$ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. The dependent variables are the individual deviations from the mean in each field of study (2-digit ISCED classification). Full set of control variables is used in each column. Additional dummy variables for the interview month are included in each column.

Table A.3
Job market prospects and student effort (IV) - Robustness check.

	(1) Very good job prospects	(2) Self-assessed effort	(3) log(Self-study (term))
Unemployment inflow	−0.180***		
	(0.03)		
Very good job prospects		0.660***	0.336*
		(0.20)	(0.17)
Observations	10233	10233	10233
F statistic		34.660	34.660

Standard IV-2SLS estimations. First stage estimations in column (1), second stage estimations in columns (2) and (3); NEPS weights used; robust standard errors clustered at the cell level (industry × state) in parentheses $^+$ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Full set of control variables is used in each column. Additional dummy variables for the interview month are included in each column.

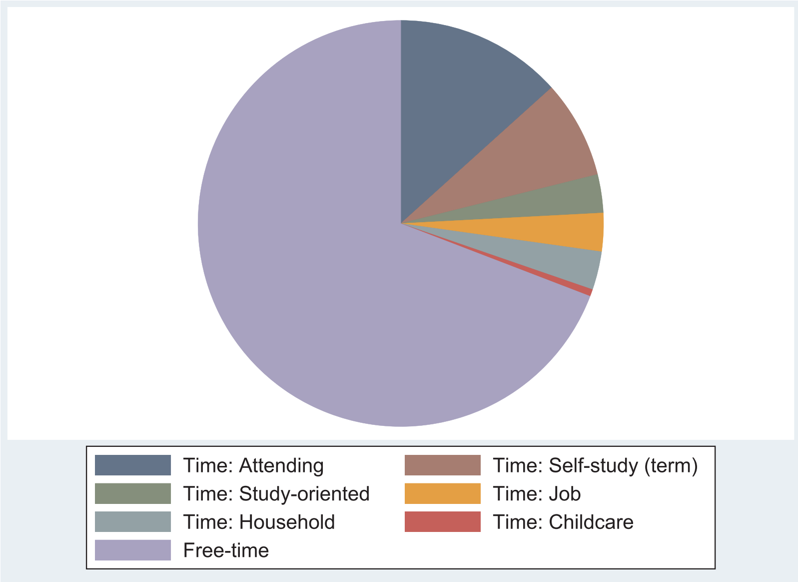

Fig. A1. Students' time allocation.
Source: NEPS. Note that free-time includes sleep and weekends.

Supplementary material

Supplementary material associated with this article can be found, in the online version

References

Aina, C., Baici, E., & Casalone, G. (2011). Time to degree: Students' abilities, university characteristics or something else? Evidence from Italy. *Education Economics, 19*(3), 311–325.

Arcidiacono, P., Bayer, P., & Hizmo, A. (2010). Beyond signaling and human capital: Education and the revelation of ability. *American Economic Journal: Applied Economics, 2*(4), 76–104.

Babcock, P., & Marks, M. (2011). The falling time cost of college: Evidence from half a century of time use data. *Review of Economics and Statistics, 93*(2), 468–478.

Bandiera, O., Larcinese, V., & Rasul, I. (2015). Blissful ignorance? A natural experiment on the effect of feedback on students' performance. *Labour Economics, 34*, 13–25.

Bedard, K. (2001). Human capital versus signaling models: University access and high school dropouts. *Journal of Political Economy, 109*(4), 749–775.

Bell, L. A., & Freeman, R. B. (2001). The incentive for working hard: Explaining hours worked differences in the US and Germany. *Labour Economics, 8*(2), 181–202.

Betts, J. R. (1996). What do students know about wages? Evidence from a survey of undergraduates. *Journal of Human Resources, 31*(1), 27–56.

Bishop, J. H., & Wößmann, L. (2004). Institutional effects in a simple model of educational production. *Education Economics, 12*(1), 17–38.

Block, J., Goerke, L., Millán, J. M., & Román, C. (2014). Family employees and absenteeism. *Economics Letters, 123*(1), 94–99.

Blossfeld, H.-P., Roßbach, H.-G., & von Maurice, J. (2011). Education as a lifelong process – the German National Educational Panel Study (NEPS). *Zeitschrift für Erziehungswissenschaft, 14*.

Bonesrønning, H., & Opstad, L. (2015). Can student effort be manipulated? Does it matter? *Applied Economics, 47*(15), 1511–1524.

Bonnard, C., Giret, J.-F., & Lambert-Le Mener, M. (2014). Educational intentions, cognitive skills and earnings expectations of french undergraduates. *Applied Economics Letters, 21*(18), 1293–1296.

Botelho, A., & Pinto, L. C. (2004). Students' expectations of the economic returns to college education: Results of a controlled experiment. *Economics of Education Review, 23*(6), 645–653.

Bound, J., Lovenheim, M. F., & Turner, S. (2012). Increasing time to baccalaureate degree in the United States. *Education Finance and Policy, 7*(4), 375–424.

Bratti, M., & Staffolani, S. (2013). Student time allocation and educational production functions. *Annals of Economics and Statistics, 111/112*, 103–140.

Brewer, D. J., & McEwan, P. J. (2010). *Economics of education.* Elsevier.

Brodaty, T., Gary-Bobo, R. J., & Prieto, A. (2014). Do risk aversion and wages explain educational choices? *Journal of Public Economics, 117*, 125–148.

Brunello, G., Lucifora, C., & Winter-Ebmer, R. (2004). The wage expectations of European business and economics students. *Journal of Human Resources, 39*(4), 1116–1142.

Brunello, G., & Winter-Ebmer, R. (2003). Why do students expect to stay longer in college? evidence from europe. *Economics Letters, 80*(2), 247–253.

Card, D. (1995). Earnings, schooling, and ability revisited. In S. Polachek (Ed.). *Research in labor economics vol. 14* (pp. 23–48). .

Chadi, A., & Goerke, L. (2018). Missing at work – sickness-related absence and subsequent job mobility markets. *Journal of Economic Behavior & Organization, 153*(9), 153–176.

Chadi, A., & de Pinto, M. (2018). Selecting successful students? Undergraduate grades as an admission criterion. *Applied Economics, 50*(28), 3089–3105.

Chevalier, A., Dolton, P., & Lührmann, M. (2018). Making it count: Incentives, student effort and performance. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 181*(2), 323–349.

Chevalier, A., Harmon, C., Walker, I., & Zhu, Y. (2004). Does education raise productivity, or just reflect it? *Economic Journal, 114*(499), F499–F517.

Cornelißen, T., Himmler, O., & Koenig, T. (2011). Perceived unfairness in ceo compensation and work morale. *Economics Letters, 110*(1), 45–48.

De Fraja, G., & Landeras, P. (2006). Could do better: The effectiveness of incentives and competition in schools. *Journal of Public Economics, 90*(1), 189–213.

De Fraja, G., Oliveira, T., & Zanchi, L. (2010). Must try harder: Evaluating the role of effort in educational attainment. *Review of Economics and Statistics, 92*(3), 577–597.

Delaney, L., Harmon, C., & Ryan, M. (2013). The role of noncognitive traits in undergraduate study behaviours. *Economics of Education Review, 32*, 181–195.

Di Pietro, G., & Cutillo, A. (2008). Degree flexibility and university drop-out: The Italian experience. *Economics of Education Review, 27*(5), 546–555.

Dolton, P., Marcenaro, O. D., & Navarro, L. (2003). The effective use of student time: A stochastic frontier production function case study. *Economics of Education Review, 22*(6), 547–560.

Easterlin, R. A. (2001). Income and happiness: Towards a unified theory. *Economic Journal, 111*(473), 465–484.

Ehlers, T., & Schwager, R. (2016). Honest grading, grade inflation, and reputation. *CESifo Economic Studies, 62*(3), 506–521.

Ewers, M., & Zimmermann, F. (2015). Image and misreporting. *Journal of the European Economic Association, 13*(2), 363–380.

Frazis, H. (2002). Human capital, signaling, and the pattern of returns to education. *Oxford Economic Papers, 54*(2), 298–320.

Frey, B. S., Benesch, C., & Stutzer, A. (2007). Does watching TV make us happy? *Journal of Economic Psychology, 28*(3), 283–313.

Garibaldi, P., Giavazzi, F., Ichino, A., & Rettore, E. (2012). College cost and time to complete a degree: Evidence from tuition discontinuities. *Review of Economics and Statistics, 94*(3), 699–711.

Gary-Bobo, R. J., & Trannoy, A. (2008). Efficient tuition fees and examinations. *Journal of the European Economic Association, 6*(6), 1211–1243.

Girard, Y., Hett, F., & Schunk, D. (2015). How individual characteristics shape the structure of social networks. *Journal of Economic Behavior & Organization, 115*, 197–216.

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The homecoming of american college women: The reversal of the college gender gap. *Journal of Economic Perspectives, 20*(4), 133–156.

Grant, D. (2007). Grades as information. *Economics of Education Review, 26*(2), 201–214.

Grave, B. S. (2011). The effect of student time allocation on academic achievement. *Education Economics, 19*(3), 291–310.

Groot, W. (2000). Adaptation and scale of reference bias in self-assessments of quality of

life. *Journal of Health Economics, 19*(3), 403–420.
Gunnes, T., Kirkebøen, L. J., & Rønning, M. (2013). Financial incentives and study duration in higher education. *Labour Economics, 25*, 1–11.
Gyimah-Brempong, K., & Gyapong, A. O. (1991). Characteristics of education production functions: An application of canonical regression analysis. *Economics of Education Review, 10*(1), 7–17.
Huntington-Klein, N. (2015). Subjective and projected returns to education. *Journal of Economic Behavior & Organization, 117*, 10–25.
Ichino, A., & Riphahn, R. T. (2005). The effect of employment protection on worker effort: Absenteeism during and after probation. *Journal of the European Economic Association, 3*(1), 120–143.
Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *Quarterly Journal of Economics, 125*(2), 515–548.
Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics, 17*(2), 303–316.
Kalenkoski, C. M., & Pabilonia, S. W. (2010). Parental transfers, student achievement, and the labor supply of college students. *Journal of Population Economics, 23*(2), 469–496.
Kroch, E. A., & Sjoblom, K. (1994). Schooling as human capital or a signal: Some evidence. *Journal of Human Resources, 29*(1), 156–180.
Krohn, G. A., & O'Connor, C. M. (2005). Student effort and performance over the semester. *Journal of Economic Education, 36*(1), 3–28.
Lackner, M., Stracke, R., Sunde, U., & Winter-Ebmer, R. (2015). Are competitors forward looking in strategic interactions? Evidence from the field. *IZA Discussion Paper No. 9564*.
Leuven, E., Oosterbeek, H., & van der Klaauw, B. (2010). The effect of financial rewards on students' achievement: Evidence from a randomized experiment. *Journal of the European Economic Association, 8*(6), 1243–1265.
Light, A., & Strayer, W. (2000). Determinants of college completion: School quality or student ability? *Journal of Human Resources, 35*(2), 299–332.
Löfgren, C., & Ohlsson, H. (1999). What determines when undergraduates complete their theses? Evidence from two economics departments. *Economics of Education Review, 18*(1), 79–88.
Mankiw, N. G. (1988). Imperfect competition and the Keynesian cross. *Economics Letters, 26*(1), 7–13. https://doi.org/10.1016/0165-1765(88)90043-2.
Metcalfe, R., Burgess, S., & Proud, S. (2019). Students effort and educational achievement: Using the timing of the World Cup to vary the value of leisure. *Journal of Public Economics, 172*, 111–126.
Michaelis, J., & Schwanebeck, B. (2016). Examination rules and student effort. *Economics Letters, 145*, 65–68.
Nash, R. (2001). Class, 'ability' and attainment: A problem for the sociology of education. *British Journal of Sociology of Education, 22*(2), 189–202.
Non, A., & Tempelaar, D. (2016). Time preferences, study effort, and academic performance. *Economics of Education Review, 54*, 36–61.
Odermatt, R., & Stutzer, A. (2019). (Mis-)predicted subjective well-being following life events. *Journal of the European Economic Association, 17*(1), 245–283.
OECD (2013). Education at a glance 2013: OECD indicators. *OECD Publishing*.
Oettinger, G. S. (2002). The effect of nonlinear incentives on performance: evidence from Econ 101. *Review of Economics and Statistics, 84*(3), 509–517.
Polachek, S. W., Kniesner, T. J., & Harwood, H. J. (1978). Educational production functions. *Journal of Educational Statistics, 3*(3), 209–231.
Reichert, A. R., Augurzky, B., & Tauchmann, H. (2015). Self-perceived job insecurity and the demand for medical rehabilitation: Does fear of unemployment reduce health care utilization? *Health Economics, 24*(1), 8–25.
Sajaia, Z. (2008). Bioprobit: Stata module for bivariate ordered probit regression. *Statistical Software Components*.
Stinebrickner, R., & Stinebrickner, T. R. (2003). Working during school and academic performance. *Journal of Labor Economics, 21*(2), 473–491.
Stinebrickner, R., & Stinebrickner, T. R. (2008). The causal effect of studying on academic performance. *BE Journal of Economic Analysis & Policy, 8*(1).
Stinebrickner, R., & Stinebrickner, T. R. (2014). A major in science? initial beliefs and final outcomes for college major and dropout. *Review of Economic Studies, 81*(1), 426–472.
van der Klaauw, B., & van Vuuren, A. (2010). Job search and academic achievement. *European Economic Review, 54*(2), 294–316.
Webbink, D., & Hartog, J. (2004). Can students predict starting salaries? Yes!. *Economics of Education Review, 23*(2), 103–113.
Wolpin, K. I. (1977). Education and screening. *American Economic Review, 67*(5), 949–958.
Wolter, S. C. (2000). Wage expectations: A comparison of Swiss and US students. *Kyklos, 53*(1), 51–69.
Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data.* MIT Press.