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The Expected (Signaling) Value of Higher Education

Abstract

This paper explores students' expectations about the returns to completing higher education and provides first evidence on perceived signaling and human capital effects. We elicit counterfactual labor market expectations for the hypothetical scenarios of leaving university with or without a degree certificate among a large and diverse sample of students at different stages of higher education. Our findings indicate substantial perceived returns to higher education. Moreover, using within-individual fixed effects models, we document substantial expected labor market returns from signaling, whereas perceived productivity-enhancing (human capital) returns seem to be less pronounced. Over the expected course of career, we find lasting education premia as well as evidence consistent with employer learning.

JEL-Codes: I210, I230, I260, J240, J310, J320, J440.

Keywords: higher education, returns to education, signaling, educational attainment, licensing, employer learning.

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1 Introduction

Higher education is a major determinant of labor earnings as university graduates earn substantially more over the life cycle than individuals with a high-school degree (Cunha, Karahan, and Soares, 2011; Piopiunik, Kugler, and Wößmann, 2017; OECD, 2017). The importance of education for labor market outcomes is rationalized in economic theory (Becker and Chiswick, 1966; Mincer, 1958, 1974) and has been documented in a vast body of empirical literature (for reviews see, e.g., Card, 1999; Patrinos and Psacharopoulos, 2020). Moreover, many recent papers show that individuals are aware of existing returns and adopt their educational decision-making accordingly (McMahon and Wagner, 1981; Manski, 2004; Delavande and Zafar, 2019).

The sources of the education premium are less well understood. According to the human capital hypothesis (Becker, 1962; Schultz, 1963; Mincer, 1974) education augments productivity because individuals acquire knowledge and useful skills during their studies. Contrary to this, the signaling hypothesis pioneered by Spence (1973) and Stiglitz and Weiss (1990) advocates that education is merely a signal of productivity. Here, the (psychic) costs of education correlate with worker productivity such that a separating equilibrium emerges where high-productivity individuals use education as a signal to earn higher wages and firms screen workers for their education to attract high-productivity-type workers.[1]

The corresponding empirical evidence on the relative importance of human capital versus signaling effects for (higher) education premia remains largely inconclusive (Patrinos and Psacharopoulos, 2020). While some studies report findings in support of the human capital hypothesis (e.g. Layard and Psacharopoulos, 1974; Chevalier et al., 2004; Kroch and Sjoblom, 1994; Aryal, Bhuller, and Lange, 2019) others report substantive evidence of signaling effects (Hungerford and Solon, 1987; Jaeger and Page, 1996; Park, 1999; Bedard, 2001; Chatterji, Seaman, and Singell Jr, 2003; Caplan, 2018). This discrepancy arises because both theories are observationally equivalent: *Ex-post*, individuals with education credentials are more productive, which entails a positive relation between education and wages.[2]

[1]A third hypothesis states that (higher) education premia arise because university attendance is a screening or selection device that induces students to resolve uncertainty about their individual returns. According to this presumption, only those students with sufficiently large returns decide to finish a degree (Chiswick, 1973; Lange and Topel, 2006).

[2]For a long time, this identification problem seemed insurmountable. As an example, Lang and Kropp (1986) write: "[M]any members of the profession maintain (at least privately) that these hypotheses cannot be tested against each other and that the debate must therefore by relegated to the realm of ideology." See also Huntington-Klein (2020).

In this paper, we circumvent this identification problem and provide first evidence on the perceived *ex-ante* signaling value to higher education. In particular, we ask two questions: Do students anticipate considerable premia to obtaining higher education? If so, do they ascribe them to the human capital acquired or the signaling value of the degree certificate?

To answer these questions, we have collected novel data on subjective pecuniary and non-pecuniary returns to finishing higher education in a large sample of students currently enrolled at a university or college of applied sciences in Germany. We elicit expected wage information among individuals who are at different stages of higher education for the hypothetical scenarios of leaving university with or without a degree certificate. Besides, the data comprise information on expected job satisfaction, the probability of finding a suitable job, expected working hours, and a large array of background variables. All expectations were elicited for the time when individuals start working and at two later points in the life cycle (at the age of 40 and 55). The data thus allow us to circumvent selection and estimate *ex-ante within-individual* graduation premia as well as to distinguish between the *perceived* signaling and human capital values of higher education.

The analysis proceeds in three steps. First, we provide general evidence on the expected returns to continued higher education, including estimates of the perceived lifetime return on investment and the perceived internal rate of return. Second, using expected wages for counterfactual scenarios of leaving university with or without a degree, we estimate within-person fixed effects models to obtain perceived wage and non-wage (job satisfaction, probability of finding a suitable job) signaling and human capital values of education. As part of this analysis, we also unveil the perceived long-term development of the graduation premium, i.e., the expected persistence of signaling and the respective importance of employer learning. Third, we investigate heterogeneities in the signaling value and the importance of returns for leaving university without a degree.

Our estimates for master's students indicate high perceived individual returns to degree completion, with an average discounted lifetime return of €334,400. Moreover, the model parameters from a within-person fixed effects analysis suggest that signaling yields a 20 percent return in terms of starting wages, more than a standard deviation in terms of job satisfaction, and more than half of a standard deviation regarding appropriate employment. At the same time, the estimated human capital value is very small and mostly not significantly different from zero. We thus observe a considerable perceived labor market advantage of an individual who recently received a credential over someone who is just about to receive it. We also find lasting effects of the graduation signal, meaning that even in the long term a student expects to earn more in the graduation scenario compared to the scenario of leaving university without a degree despite perceived employer learning. Finally, by exploring subjective leaving probabilities, we find that the expected earnings premium plays a rather small role in the choice to leave university without a degree as compared to variables that proxy for student satisfaction or psychic costs. This finding is congruent with a large body of literature documenting small educational choice responses to monetary incentives (e.g., Arcidiacono, 2004; Beffy, Fougere, and Maurel, 2012; Wiswall and Zafar, 2015). It is also in line with the signaling hypothesis, which implies homogeneous returns to finishing a certain degree, but differential costs of studying. In other words, the decision to select out of education should be driven by the (psychic) cost of education only, and not the potential earnings gain from finishing.

Whether education premia arise due to human capital augmentation or signaling holds important implications for young people's motivation to obtain higher education, as well as their educational decision-making. If education merely increases productivity, then for individuals who want to work in a high-productivity job or position, attending higher education (or at least studying the material) is without alternative. However, if education only relates to signaling, high-productivity types will only obtain a degree if there is no other, cheaper (but equally credible) way to document their future productivity. Similarly, if signaling prevails, leaving a higher educational institution (shortly) before obtaining the degree is very costly in terms of later wages, while it should matter little under the human capital hypothesis.[3] The aim of this paper is thus to explore perceived signaling and human capital values as they can determine students' decision-making. Yet, our findings may have more general implications, given a high average accuracy of reported wage expectations in our data.

The analysis in this paper builds upon and extends prior work regarding the importance of so-called graduation premia, signaling, diploma, or sheepskin effects (see, e.g., Weiss, 1995; Lange and Topel, 2006, for reviews). Part of this research relies on a matching assumption for identification, as researchers regress wages on the number of years of schooling and degree attainment and then interpret the wage differential between degree and non-degree workers conditional on years of schooling as signal-

[3]The type of regime also has implications for societal investments. For example, if education augments human capital, society may subsidize it to reap positive externalities in the form of productive worker interactions, better citizenship, or knowledge spillovers. If education is simply a means to convey information, society might as well leave it to the individual to pay for it, unless it effectively reduces uncertainty about the quality of labor input to firms, which may increase total output (Wolpin, 1977).

ing (Hungerford and Solon, 1987; Frazis, 1993; Jaeger and Page, 1996; Park, 1999; Altonji and Pierret, 2001; Ferrer and Riddell, 2002).[4] Another part uses instruments or discontinuities to identify the graduation premium for individuals at the margin (see, e.g., Acemoglu and Angrist, 1999; Tyler, Murnane, and Willett, 2000; Clark and Martorell, 2014; Barrera-Osorio and Bayona-Rodríguez, 2019). Similarly, some papers exploit changes in the curriculum, years, or intensity of schooling to investigate exogenous changes in the human capital accumulation process on wages (see, e.g., Arteaga, 2018; Goodman, 2019). Our approach complements this literature in two respects. First, we only look at the supply side, i.e., by estimating signaling effects among (future) labor market participants, thus abstracting from equilibrium effects. Second, we estimate the graduation premium from within-person variation, enabling us to estimate average instead of local effects.

This paper also adds in general to the literature on subjective expectations. In particular, it relates to work on the role of expectations of returns when making educational decisions, such as starting tertiary education (Boneva and Rauh, 2017; Attanasio and Kaufmann, 2014, 2017), major and occupation choice (Arcidiacono et al., 2017; Wiswall and Zafar, 2015) or completing tertiary education (Stinebrickner and Stinebrickner, 2014; Wiswall and Zafar, 2016; Hastings et al., 2016). While much of this work relies on data from small, selective samples, we can rely on a dataset that allows us to make statements about a substantive population of students.

In addition, our findings pertain to a large body of literature on employer learning (Farber and Gibbons, 1996; Altonji and Pierret, 2001). This research investigates the extent to which statistical discrimination by employers based on degree signals fades over time as employers learn about the true underlying productivity of new employees (Farber and Gibbons, 1996; Lange, 2007). It also shows that employer learning may differ by the type of degree or the observability of educational content (Arcidiacono, Bayer, and Hizmo, 2010; Bauer and Haisken-DeNew, 2001; Aryal, Bhuller, and Lange, 2019). We add to this strand of research by providing insights into the extent to which individuals anticipate signaling and employer learning effects to affect their wages in the longer run.

Finally, our paper relates to research on the role of psychic costs and non-monetary outcomes for educational decision-making (Cunha, Heckman, and Navarro, 2005; Heckman, Lochner, and Todd, 2006; Jacob, McCall, and Stange, 2018; Boneva and Rauh, 2017). This literature documents that both psychic costs and non-pecuniary factors are important determinants of educational decision-making, which

[4] See also Fang (2006) for a structural model of education choices to disentangle signaling and human capital effects.

is in line with our findings that the perceived monetary returns matter little for the decision to complete a degree.

The remainder of the paper is organized as follows. In section 2, we provide information on the data collection procedure, describe our sample and main measures. Section 3 provides descriptive insights into the data. Subsequently, section 4 contains our empirical strategy and main results for the perceived signaling value. Section 5 then tests two implications of the signaling theory. Finally, section 6 concludes.

2 Data

This section provides detailed information on our sample and questionnaire measures. We start by describing the data collection procedure, before we report on our measures related to expected labor market outcomes, future employment, university experience and various background characteristics. Finally, we present summary statistics of the main background variables.

2.1 Data collection

Our sample was recruited as part of the German student study "Fachkraft 2020" (now called 'Fachkraft 2030").[5] Students on the mailing list of a popular nationwide job board were contacted via email and asked to complete an online questionnaire with items related to future labor market expectations, current study experiences, university dropout and a broad range of background characteristics.[6] The surveys were conducted in September 2014 and March 2015 and participation in the study was incentivized using Amazon vouchers amounting to €5,000.

2.2 Measures

Labor market expectations As we are interested in individuals' expected labor market outcomes for different studying scenarios, we obtain students' counterfactual labor market expectations. Specifically, we elicit job prospects for two different scenarios: (i) when students graduate from their preferred major (graduating scenario) and (ii) when they leave university without obtaining any further academic degree (leaving scenario), see appendix section B for the survey items. As we exploit the

[5]See Seegers et al. (2016) for more information.

[6]The data were collected via the job board jobmensa.de operated by Studitemps GmbH. It is the largest platform for student jobs in Germany.

fact that students are in different stages of their studies, we assume that for the leaving scenario students think about leaving university immediately, and hence their current semester is seen as the semester in which they would hypothetically leave. For students in a later semester of studying, this is consequential, as there is not much time left in which they could leave university. For students at the start of their studies, it is reasonable to assume that in the leaving scenario students would expect to leave university immediately due to the high opportunity costs of studying. For each scenario, students indicate their expectations with respect to gross yearly labor earnings, weekly working hours, the probability of finding a suitable job, and job satisfaction, where the latter is measured on a scale from 1 to 10.[7] From the specified earnings and working hours, we construct expected hourly wages and full-time wages.

Moreover, in order to gain a better understanding of the development of perceived labor market expectations over the life course, all wage expectations were elicited for three different points in time: at the age when a person first starts working, at the age of 40 and 55.[8] With this information, we compute lifetime wage trajectories by assuming a standard Mincer-type earnings function where wages ($W_i^c(t)$) are a quadratic function of work experience:

$$W_i^c(t) = \alpha_i^c + \beta_i^c experience_i^c(t) + \gamma_i^c(experience_i^c(t))^2 \tag{1}$$

Experience in time t is calculated by deducting the expected age at labor market entry from the age at time t.[9] We solve equation (1) for each individual i and counterfactual c to obtain scenario- and individual-specific parameters β_i^c and γ_i^c.[10] Then we use these parameters to compute expected wages for each year of a person's working life for both the graduating and leaving scenarios.

In accordance with the literature (see Polachek et al., 2008, for a review), concave wage trajectories (in experience) are most prevalent in our data with 69.9 percent for the graduating scenario and 45.3 percent for the leaving scenario (see appendix figure A2). Convex wage growth pattern come in second, with 24.4 percent (graduating) and 31.8 percent (leaving) respectively. Only 5.5 percent of students expect a linear increase in earnings after graduating, and 21.7 percent after leaving. A small

[7] In the survey students were asked for the probability of *not* finding a suitable job. However, for readability we recode this as the job-finding probability.

[8] Expected job satisfaction and the probability of finding a suitable job were only elicited for labor market entry and the age of 40, not for the age of 55.

[9] Students indicated their current age and how long they still need to study until they finish their degree. With this information, we were able to calculate the expected age at labor market entry.

[10] See appendix figure A1 for the distribution of parameters β and γ.

proportion remains unclassified, which mainly originates from expected wage developments that decrease over time. For the scenario of leaving university we observe more linear and convex patterns, which is mainly due to lower initial wage growth (see appendix figure A3). This observation is in line with a body of literature showing that actual wage growth is steeper for higher levels of schooling (Belzil, 2008; Dustmann and Meghir, 2005).

Future employment Respondents were asked about the profession they plan to pursue after graduating from their current studies. They could choose out of 429 predefined occupations or make use of a free text field. This information allows us to classify whether people plan to pursue a profession that is legally regulated, meaning that individuals need to have a license in the form of a (specific) degree to pursue this occupation. We follow the classification of the German federal employment agency for regulated professions (Bundesagentur für Arbeit, 2020). Typical occupations for which this applies are physicians, lawyers or engineers. In addition, we elicit whether individuals aim for a civil servant job, i.e., with fixed wage regulations according to experience and education. This information allows us to control for a licensing effect after graduation.

University experience The survey also contains questions about various aspects of students' university experience. First, with respect to the study phase, we asked which degree respondents aim to obtain. In addition, we asked how many semesters they have studied, both with respect to their current studies as well as overall, and how many semester they still expect to need to finish their current degree.[11] Second, respondents were asked to report their study subject from a list of fifteen study fields. We group these subjects into five main categories: medicine/health, STEM, law, economics, and humanities/social sciences. Third, to obtain a measure of performance, we elicited students' grade point average. Furthermore, we asked them to estimate their perceived relative position in the distribution of all students regarding academic ability and work-related ability on a scale from 0 to 100. Fourth, to better understand the relevance of the leaving scenario, we asked students about their perceived probability of leaving university *without any further degree*, where this probability excludes switching to an alternative university study. Finally, we elicited their overall satisfaction with their studies.

[11] In Germany, only roughly 30% of all students obtain a degree in regular study time (Destatis, 2018). Often internships, side jobs or stays abroad prolong the study time. We thus obtained both semesters studied and semesters left to study to approximate the students' current stage of studying.

Background characteristics We also collected data on a broad range of individual characteristics, such as gender, age, migrant background, and state of residence. Moreover, we inquired about respondents' high-school GPA to have information on pre-university performance. Finally, we asked individuals to state whether neither, one, or both of their parents attended university, which is a proxy for socioeconomic background. For an overview on the most relevant variables, see table 1.

2.3 Sample characteristics

After dropping observations with implausible wage returns or missing explanatory variables, we obtain a sample of 6,306 students.[12] Table 1 provides summary statistics of the main background variables for our sample and for the entire population of students in Germany in the 2014/2015 academic year. The table shows that our sample closely compares to the overall population of German students in terms of age, migration background, region, degree type and high-school GPA. An exception is that females are slightly overrepresented, potentially due to higher responsiveness to surveys among females in general (Molarius et al., 2019). In addition, there are 29.3% economics students in our sample, which is 15 percentage points more than the population share in this subject category. This higher share of economics majors mainly comes at the cost of a lower fraction of students in humanities, social sciences, and law. This imbalance might reflect that all students were approached via a job agency and having a side job could be more common for economics students. In our analysis, we take these differences into account, see section 4.

Our data vary in terms of respondents' study phase. For respondents aiming to obtain a master (bachelor) degree, 31.7% (10.0%) are in semester 1-2, 37.4% (26.0%) in semester 3-4, 19.6% (27.4%) in semester 5-6 and 11.3% (36.6%) in their 7th or higher semester. This variation is essential to estimate the value of human capital accumulation.

3 Descriptive evidence

In this section, we first characterize the wage and non-wage returns that students perceive from both graduating and leaving university without a degree. Then, we provide descriptive evidence on where these returns originate from.

[12]See section C in the appendix for more information on the data-cleaning procedure.

Table 1: Summary statistics

		Our sample	Student cohort 2014/15*
Age		23.5	23.4
Male (%)		47.1	52.2
Migration background (%)		16.7	16.2
Federal state(%)	Baden-Wuerttem.	11.4	13.2
	Bayern	17.0	13.6
	Berlin	7.1	6.3
	Brandenburg	2.0	1.8
	Bremen	1.7	1.3
	Hamburg	2.8	3.6
	Hessen	8.7	8.8
	Mecklenburg-Vorp.	1.5	1.4
	Niedersachsen	7.1	7.1
	Nordrhein-Westfalen	23.3	26.9
	Rheinland-Pfalz	4.8	4.5
	Saarland	0.5	1.1
	Saxony	4.5	4.2
	Saxony-Anhalt	2.5	2.0
	Schleswig-Holstein	2.8	2.1
	Thueringen	2.4	1.9
Bsc. student (%)		77.0	78.1
Subject (%)	Medicine	5.7	6.0
	STEM	37.4	39.2
	Law	1.3	4.9
	Econ.	29.3	15.5
	Human./Social	26.3	34.5
High-school GPA		2.42	2.45
Observations		6,306	2,698,910

Notes: Table 1 compares the summary statistics of several background characteristics between our sample and the overall German student cohort in 2014/15. In Germany, the best grade is 1.0 and the worst passing grade is 4.0. The statistics for the total student cohort originate from Destatis (2020) and Govdata (2020).

3.1 Perceived wage returns

We start out by comparing the indicated perceived graduation wage to the perceived university-leaving wage at the time of labor market entry. The top panel of figure 1 plots the density of these two measures. In addition to substantial variation in expected starting wages between individuals, the graph shows that students expect their leaving wages to be much lower than their graduation wages. On average, students expect €27,400 of yearly earnings when leaving university instead of €38,000 when graduating, with the averages being weighted by major and gender. The perceived graduation wage average fits well with the observed labor market entry wage for university graduates, which in 2014 amounted to €36,600 (Destatis, 2017). Furthermore, the patterns of earnings expectations between university majors and gender are plausible, with on average higher expected earnings for males and STEM majors (see appendix figure A4). Estimates of future earnings are also fairly accurate, as observed yearly earnings at age 60 after obtaining a university degree were €60,700 in 2014, compared to €69,200 in our sample (Destatis, 2017). These long term expectations are reasonable despite a 15% higher expected wage compared to current observed wages given that a rising skill premia will likely lead to higher wages among future cohorts of experienced workers with university degree (the ones in our sample), as compared to current ones.[13]

We proceed by computing lifetime earnings return, that is, the discounted sum of wage income after graduating minus wages earned when leaving minus potential study costs. Furthermore, we calculate the internal rate of return, namely the discount rate that would make an individual indifferent between finishing and leaving university. We thus solve the following two equations:

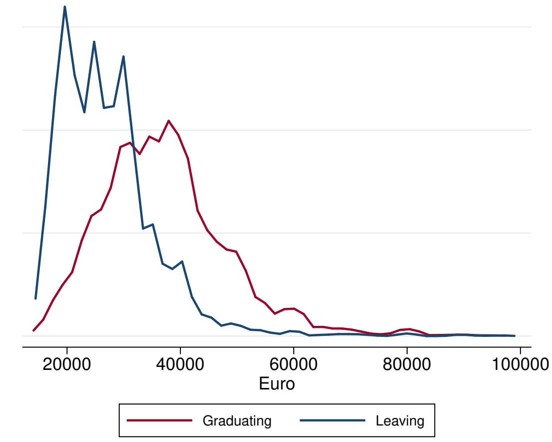
$$V_i^* = \sum_{t=t_i^f}^{65} \delta^{t-t_i^f} W_i^f(t) - \sum_{t=t_i^l}^{65} \delta^{t-t_i^l} W_i^l(t) - \sum_{t=t_i^l}^{t_i^f} \delta^{t-t_i^l} C_i \tag{2}$$

$$\sum_{t=t_i^l}^{65} \frac{W_i^f(t) - W_i^l(t)}{(1+\rho)^{(t-t_i^l)}} = \sum_{t=t_i^l}^{t_i^f} \frac{C_i}{(1+\rho)^{(t-t_i^l)}} \tag{3}$$

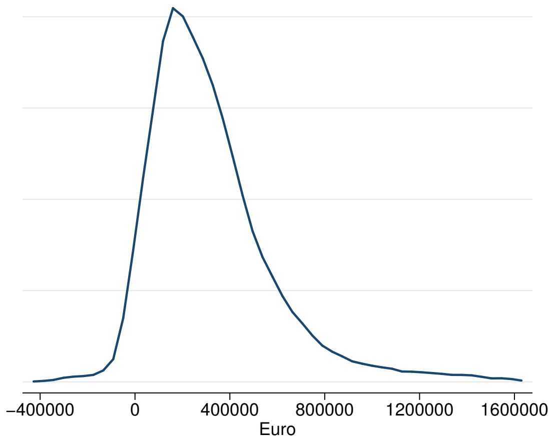
where V_i^* are the lifetime returns for individual i and $W_i^f(t)$ and $W_i^l(t)$ indicate expected wages after finishing studies (f) and leaving (l) at time t. Accordingly, t_i^f and t_i^l is the age at which an individual i is expected to start working when she finishes studying or leaves university. C_i are the yearly study costs an individual

[13]We cannot compare the expected leaving wages to observed values, as any observed measure would be heavily influenced by selection.

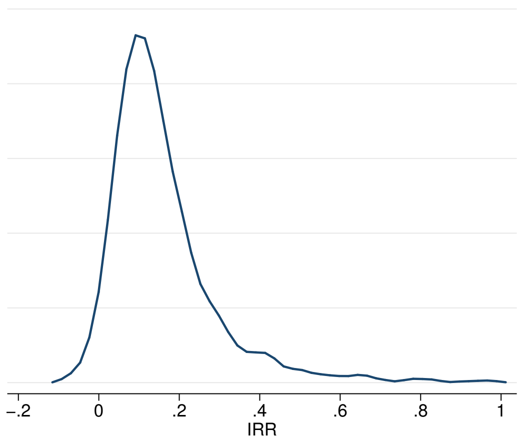
Figure 1: Density of starting wage and returns



(a) Expected starting wage by scenario



(b) Life time wage returns



(c) Internal rate of return

Notes: Figure 1 panel A shows the density of the expected wage at labor market entry for graduating and leaving university without a degree. Panel B shows the density of the lifetime wage returns, which are calculated according to equation (2). Finally, panel C portrays the density of the internal rate of return, as estimated in equation (3).

incurs, and they are assumed to stay constant over time. Study costs include only explicit costs such as tuition fees, spending for books or other materials needed and were elicited in the survey. Furthermore, in equation (2), δ is the time discount rate, which is set at 0.95. We also calculated the returns for $\delta = 1$ to estimate an upper bound for lifetime returns. In equation (3), ρ is the internal rate of return. An individual chooses to obtain a higher education degree if $V_i^* > 0$ or $\rho > 0$.

The density graphs of the return measures can be found in panels B and C of figure 1. Panel B shows that almost all respondents in our sample expect positive discounted lifetime earnings returns from graduating, with the average being around €334,400 until retirement.[14] Panel C shows a similar pattern for the estimated internal rate of return (IRR), since only 3.2 percent of all respondents expect a negative return and the average rate of return is 17.9%. Accordingly, if students in our sample face the decision whether to complete their current degree or leave university without graduating, they on average expect to encounter a 17.9% return to *completing* their studies. This percentage is substantially higher than the IRRs generally reported in the literature for the *initial* choice of starting a university study or not, e.g., the observed initial IRR within Germany in 2014 is 7.5% (OECD, 2014). First, this discrepancy is partly driven by the fact that the students in our sample have self-selected into university. Second, we observe the IRR for *completing* a degree that individuals are currently pursuing, hence students have already paid some of the direct and indirect costs of studying. It is worth mentioning that the discrepancy between initial and "course of study" IRRs points to returns mostly accruing towards the end of one's studies, while the costs are borne at the beginning. Therefore, we also look at the IRR of students who only recently started studying. For students in their first or second semester we find an IRR of 11.4%, which comes close to the observed initial IRR.

3.2 Perceived non-wage returns

Along with the wage returns of finishing a university degree, expected non-wage returns are an important labor market outcome for students (e.g. Wiswall and Zafar 2016). Figure 2 shows the expected job satisfaction and the job-finding probability when finishing and leaving university. Similar to the expected wage returns of graduating, students expect large non-wage returns to a university degree. Panel A displays substantial differences in the distribution of job satisfaction between the two scenarios. While the mean expected job satisfaction is 7.2 out of 10 for gradu-

[14] If we calculate the upper bound for the lifetime returns, setting the discount rate $\delta = 1$, the average expected return increases to €792,200.

ating, it is only 4.0 for leaving university. The density of the expected job-finding probability by the age of 40 for each scenario is displayed in panel B of figure 2. We look at the expected job-finding rate at the age of 40 instead of at labor market entry to prevent the results from being driven by the fact that many first-time employees need some time to initially find a suitable job.[15] The expected return to graduation is substantial, with a mean expected probability of finding a suitable job after graduating of 81.9% compared to 56.7% after leaving university.

3.3 Origins of returns

To gain a first insight into the perceived origins of the returns, we show descriptive evidence on the immediate graduation premium, as well as the development of expected returns after leaving university over the course of studying.

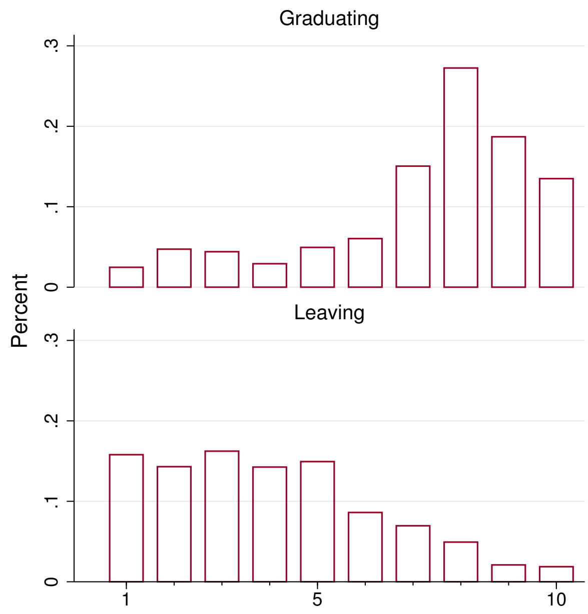
With respect to the graduation premium, we are interested in the impact of obtaining a degree certificate on students' wage expectations. For this purpose, we compare perceived starting wages after graduating to perceived starting wages when leaving university for master students who indicate being in either their last or second-last semester before finishing their studies. Restricting the descriptive comparison to a sample of students who have almost completed their degree minimizes the chance that the difference in returns over scenarios is (mainly) driven by accumulating human capital during one's studies.[16] Moreover, as we compare the wage expectations within an individual across the two scenarios, this comparison is free from selection bias. Panel A of figure 3 shows that there is a substantial difference between the average expected leaving wage and the average expected graduation wage for students in their last semester. The expected premium to graduation is 24.5%, which corresponds to €7,400 yearly gross income (€37,600 versus €30,200). This is a sizable difference, especially considering that we are only looking at master students, i.e. those who have already completed a first university degree.

In addition, we look at how the perceived returns when leaving university without a degree evolve over the course of studying, which can be interpreted as an indication of the expected accumulation of human capital. For the following comparison (and for our estimations in section 4), we assume that a higher number of semesters

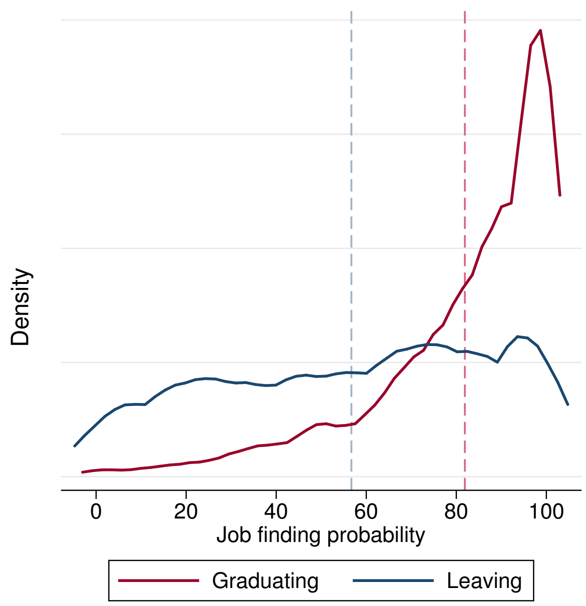
[15]The results for the job-finding probability at labor market entry are qualitatively similar, and can be found in figure A5 in the appendix.

[16]Besides, we focus on master students as they obtain an additional degree, which is different from obtaining a first academic degree, as is the case for most bachelor students. See appendix E for a more extensive explanation.

Figure 2: Density of job satisfaction and expected probability to find a suitable job



(a) Expected job satisfaction by scenario



(b) Expected prob. to find a suitable job at age 40 by scenario

Notes: Figure 2 panel A shows the distribution of expected job satisfaction at labor market entry for the scenarios of graduating and leaving university, measured on a scale from 1 to 10. The second panel displays the density of the expected probability of finding a suitable job at the age of 40 for both scenarios. The average expected job-finding probability at the age of 40 is 81.9% for graduating and 56.7% for leaving university without a degree (dashed lines).

studied is associated with a higher human capital value.[17] Panel B of figure 3 shows the perceived starting wage after leaving by number of semester studied for master students. As we compare expected leaving wages between individuals over different semesters, we control for background characteristics such as gender, major and age. According to the human capital theory, we should see an upward trend in expected leaving wages, as more productive human capital is accumulated over the course of studying, giving rise to higher expected wages when leaving university. However, we do not observe a conclusive pattern. Wages slightly increase between students who are in their first year compared to students in their second year of master studies by around €1,400, but the difference is not statistically significant. We do not observe any difference in expected leaving wages between students in their second and third year. Moreover, the magnitude of the effect is much less substantial than the premium of obtaining the degree.

4 Perceived signaling value of higher education

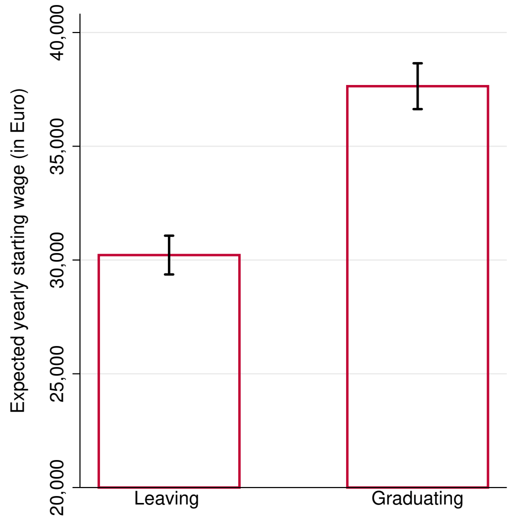
The descriptive findings strongly suggest that students expect substantial labor market returns from finishing their studies, which seems to be largely driven by a graduation premium. In this section, we estimate the perceived signaling effect of a degree and proxy the value of human capital accumulation more precisely on hands of our unique individual counterfactual expectations data.

4.1 Immediate wage returns

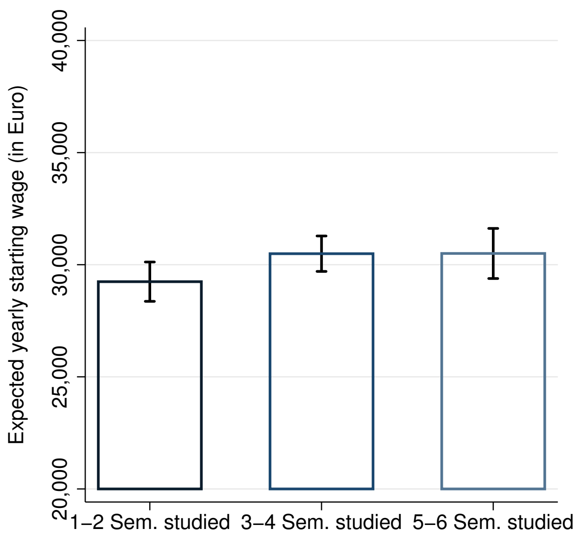
Our strategy of eliciting counterfactuals through carefully-designed survey questions allows us to estimate the effect of obtaining a degree on a within-person basis, i.e. without having to worry about other confounding factors. A growing body of literature relying on hypothetical scenarios, beliefs, and counterfactual labor expectations has shown that stated expectations and preferences tend to be close to actual realizations and informative about actual choices and behavior (see, e.g., Wiswall and Zafar 2016, Mas and Pallais 2017). Yet, even if elicited labor market expectations were biased, they are nevertheless informative about beliefs that enter the indi-

[17]This assumption is credible as in general every semester studied involves coursework, mandatory internships, writing a thesis or the like. However, there might be some students who obtain fewer or no credits in a given semester. One can imagine that an extension in study time often comes due to stays abroad, (voluntary) internships or side jobs, which can also be seen as enhancing human capital. Thus, one more semester studied should be associated with a higher or at least similar human capital compared to the previous semester, even if students take more time to study than the regular study time.

Figure 3: Graduation premium among students in their final semesters compared to development of university-leave wages



(a) Graduation premium



(b) Leaving wages by semester studied

Notes: The top panel of figure 3 shows the expected yearly starting wage for leaving university compared to graduating on a within-individual basis. It includes only master students who are in their (second to) last semester. The bottom panel compares the expected yearly starting wage for master students at different stages of their studies. As the comparison is between individuals, we control for gender, age, ability, SES, major and perceived work ability.

vidual decision-making process. Nonetheless, the considerable average accuracy of wage expectations at labor market entry portrayed in section 3 allow us to extend the interpretation of the following signaling results more generally.

Using the counterfactuals, we can identify the effect of a degree by comparing the two different scenarios on a within-person basis, eliminating the individual fixed effect. Additionally, we approximate the human capital effect by comparing leaving wages between individuals who are in different semesters of their studies and assume that human capital accumulates linearly over time.[18] As the signal is most prevalent at labor market entry, we first concentrate on the immediate returns from graduating, but we will also look at the long-term development of the graduation premium in section 4.3. Accordingly, equation (4) shows our main specification for immediate returns:

$$W_i^c = \beta_0 + \beta_1 degree_i^c + \beta_2 semesters_i^c + \gamma_i + \epsilon_i \tag{4}$$

W_i^c represents the expected yearly starting wage of individual i in scenario c, with $c = f$ for graduating and $c = l$ for leaving. In this equation, as well as in equations 5 to 7, all expectations variables used are about the time of labor market entry, and hence W_i^c stands for $W_i^c(start)$, with $t = start$ indicating the time at which individual i starts working. Moreover, $degree_i^c$ is a dummy variable indicating the graduation wage, which is one for the scenario of obtaining a degree and zero for leaving without a degree. $semesters_i^c$ indicates how many more semesters an individual still has to study to finish their degree, which is zero in the scenario of graduating.[19] The individual fixed effects are captured by γ_i, which controls for an individual's scenario invariant characteristics and ϵ_i is the error term clustered on individual level. Hence, β_1 measures the value of the degree certificate, while β_2 captures the expected wage premium for getting one semester closer to the degree.

The interpretation of the above analysis rests on the assumption that graduating results in a positive signaling value. However, it is conceivable that leaving university without a degree yields a negative signal instead. In this case, the absolute size of the signaling value that we estimate would be unaffected, but its interpretation would change. We provide a detailed account of this possibility in appendix section D.

[18]We restrict the sample to students who indicate having at most eight semesters left to study, changing the sample size to 3,945 and 1,284 for bachelor and master students, respectively. This does not affect our main results (see section 4.4).

[19]To make the estimates more comprehensive, we used a negative sign on the semester variable such that a higher (less negative) semester variable means getting closer to the degree. Of course, the coefficients are unaffected by this manipulation, whereby only the sign is positive instead of negative.

Table 2: Wage returns

	(1) Starting wage levels	(2) Starting wage logs	(3) Starting wage logs
Semesters	212.277	0.007	0.007
	(157.298)	(0.004)	(0.004)
Degree	7,099.660***	0.209***	0.203***
	(549.446)	(0.015)	(0.016)
Interaction effects:			
Licence*Degree			0.029*
			(0.016)
Civil servant*Degree			0.003
			(0.018)
Constant	30,639.636***	10.287***	10.288***
	(520.848)	(0.014)	(0.014)
N	2762	2762	2754
adj. R^2	0.461	0.506	0.507

Notes: Column 1 in table 2 shows the effects on the level of yearly starting wages, while the dependent variable in columns 2 and 3 comprises of the log starting wage. The sample only includes master students who have maximum of eight semesters left until reaching their degree. Standard errors in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Throughout the paper, we stick to the interpretation of a positive signaling value for obtaining the degree certificate, as this is most in line with the existing literature.[20] Under this assumption, β_1 can be interpreted as the (positive) signaling effect of a degree and β_2 can be interpreted as the human capital value per additional semester studied.

We estimate equation (4) separately for bachelor and master students and focus on master students throughout the main analysis, as they face less ambiguity with respect to both their own ability (Stinebrickner and Stinebrickner, 2012; Arcidiacono et al., 2016) and potential labor market outcomes (see appendix E for an extensive discussion). Table 2 shows our main results with expected starting wages as the outcome variable for master students. In column 1, we estimate the model for wage levels, whereas the other columns use log wages as the outcome variable. The first coefficient estimated in column 1 indicates that the effect of coming one semester closer to graduating is positive but small, with roughly a €210 increase in expected

[20] We believe that this is also more plausible since labor market applicants have some leeway in informing future employers about (the reasons for) leaving university without a degree. Of course, this might not always be possible, as it depends among others on the time studied, although very often applicants only include accomplishments and positive signals in their application and not failures.

yearly starting wages on average. By contrast, graduating is expected to increase returns by €7,100. Column 2 shows that this translates into a wage increase of 0.68% for an additional semester studied and 20.9% for the degree respectively. The size of the expected signaling effect is notable, especially since we only consider the returns to a master's degree, such that leaving still means being able to start working with a bachelor's degree.

Arguably, for certain (often high-paid) professions, the returns from graduating might be driven by legally-binding requirements to obtain a certain degree certificate in order to take up a specific employment. Licensing may thus capture something very distinct from future productivity. Therefore, in column 3 we include two interaction terms: first, a dummy indicating whether an individual plans to work in a legally-regulated occupation; and second, a dummy indicating whether a person plans to work as a civil servant. In Germany, many positions as a civil servant also require a completed degree and the earnings are predefined by a collective wage structure depending among others on the highest degree obtained. The results in column 3 show that the interaction term for licensed professions is positive and marginally statistically significant. Nonetheless, the effect size is relatively small and the magnitude of the signal is almost unaffected by controlling for licensing. At the same time, we do not observe an effect of planning to work as a civil servant. One explanation might be that although having a master's degree allows individuals to earn more when working in a public institution, in general the earnings potential as civil servant tends to be lower compared to the private sector.

In appendix table A1, we present the same estimates for bachelor students. The results show a similar pattern as for the master students, with a positive but small increase of expected earnings over semesters (0.62%), and a large signaling value of graduating (32.1%). It is reasonable that the effect size of graduating is stronger for bachelor students, as graduating yields their first academic degree, possibly allowing them to enter a different segment of the labor market.

4.2 Immediate non-wage returns

In addition, we estimate the fixed effects model for expected non-wage returns, namely job satisfaction and the probability of finding a suitable job. At present, little is known about the extent to which signaling expands to non-wage returns. There are two possible scenarios. First, if wage and non-wage returns are positively correlated, we would expect to see a positive signaling value for both the perceived job-finding probability and job satisfaction. Instead, if they are negatively correlated

– for example, due to compensating wage differentials (Rosen, 1974) – we would expect to see opposite or non-significant results. For the estimation of the fixed effects model, we standardize both variables across scenarios, using the value in the leaving scenario as the baseline to adjust both leaving and graduating values:

$$S_i^c = \frac{sat_i^c - \mu_{sat}^l}{\sigma_{sat}^l} \tag{5}$$

with S_i^c as the standardized outcome variable (in this case job satisfaction). Here, sat_i^c is the expected satisfaction of individual i for scenario c and μ_{sat}^l and σ_{sat}^l are the mean and standard deviation of the perceived satisfaction when leaving university.

Table 3 shows the results for the expected non-wage returns, where the first two columns examine satisfaction at labor market entry and the last two relate to the job-finding probability. For both measures, we observe similar patterns compared to wage returns. There is a large perceived graduation premium, which is statistically significant across all specifications. We observe that the degree raises expected satisfaction by 1.04 of a standard deviation, and expected job-finding probability by 0.46 of a standard deviation. At the same time, the expected human capital effect is not statistically significant, although the signs of the effects are as expected and consistent with our previous findings. Moreover, planning to enter a licensed occupation after graduation does not significantly affect expected job satisfaction. However, for the expected suitable job-finding probability licensing or becoming a civil servant substantially increases the probability. In appendix table A2, we present the findings for the non-wage returns of bachelor students. These results are similar to our main findings, where graduation yields even stronger effects, i.e., approximately a 1.5 standard deviation increase in job satisfaction, and a 0.8 standard deviation increase in the job-finding probability.

4.3 Persistence of the graduation premium

So far, our results suggest that students perceive the immediate returns from graduating to stem from signaling their ability to employers in the labor market rather than from accumulating human capital. However, in the longer run this might be different, as individuals can demonstrate their abilities and reveal their true productivity types to employers while working. As a consequence, the initial advantage of the signal might diminish over the working life. As we collected data on the expected wage returns for three points in time and computed wage expectations over the whole life span for both scenarios accordingly, we are able to examine how the initial difference between graduates and university leavers evolves over the course of

Table 3: Non-wage returns

	(1) Satisfaction	(2) Satisfaction	(3) Job finding probability	(4) Job finding probability
Semesters	0.020	0.022	0.008	0.009
	(0.026)	(0.026)	(0.018)	(0.018)
Degree	1.091***	1.039***	0.519***	0.461***
	(0.093)	(0.095)	(0.066)	(0.067)
Interaction effects:				
Licence*Degree		0.153		0.125*
		(0.093)		(0.069)
Civil servant*Degree		0.087		0.148**
		(0.108)		(0.074)
Constant	0.067	0.073	0.025	0.032
	(0.088)	(0.088)	(0.062)	(0.062)
N	2762	2754	2762	2754
adj. R^2	0.424	0.424	0.240	0.243

Notes: Columns 1 and 2 in table 3 show the effects on expected job satisfaction at labor market entry, while the dependent variable in columns 3 and 4 is the expected probability of finding a suitable job. Both satisfaction and job-finding probability are expressed in standard deviations according to equation (5). The sample only includes master students who have maximum of eight semesters left until they reach their degree. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

career. In addition, we can investigate heterogeneities in the long term development by perceived work ability to assess the degree of perceived employer learning (see, e.g., Farber and Gibbons, 1996; Lange and Topel, 2006; Aryal, Bhuller, and Lange, 2019, for a discussion and evidence regarding actual wage outcomes) and the extent to which it may outweigh the signaling effect in the long run.

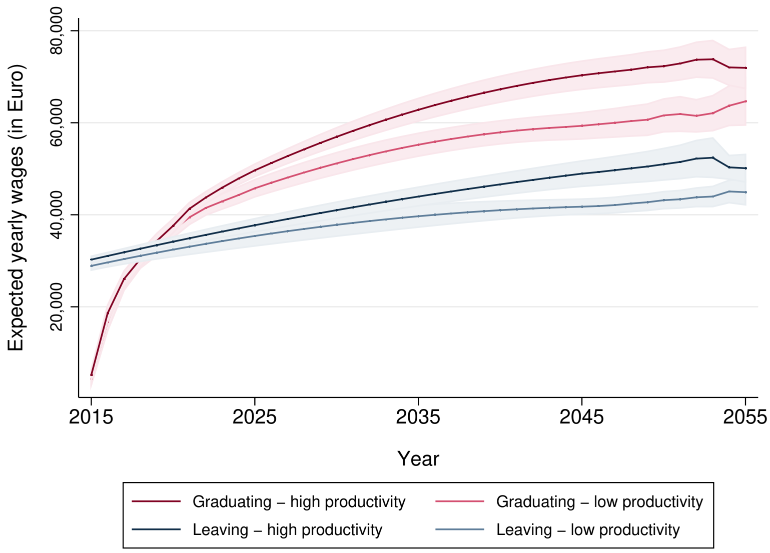
Figure 4 displays the development of expected wages after graduating (red lines) and after leaving university without a degree (blue lines), where the darker (top) lines of each color resemble the upper 50% of the perceived work ability distribution and the lighter (bottom) lines resemble the bottom 50% of perceived work ability. The colored areas around the lines indicate the 95% confidence intervals. We use the indicated perceived work ability of each individual as a proxy for later (perceived) productivity in the labor market.

From figure 4 we can derive several conclusions about the persistence of graduation premia, employer learning, and long-run expected wage dynamics. First, graduation premia matter in the long-run, independent of productivity type, as students expect to earn more in absolute terms at every point in time as graduates than as university leavers. In fact, from all master students only 8.9 percent expect to be able to diminish part of the wage gap between the graduating and leaving scenario at some point in their career. Moreover, merely 4.2 percent of master students belief they can fully close the gap, mostly towards the end of their careers (see appendix figure A6). For bachelor students these percentages are even lower, with 6.5 and 2.6 percent respectively. Second, figure 4 provides evidence consistent with employer learning. At the start of working life, there is only little difference between high- and low-productivity types in both scenarios, which supports the main result of our paper, namely that students expect a signaling effect to drive the initial returns of graduating. When a degree is mainly a way to signal one's type, productivity is initially unobserved by employers. Moreover, as the signal should have the same value to everyone who obtains it, returns should be similar for all productivity types at the start of career. Then, as employers learn more about individual ability, the difference between the low- and high-ability employees within both scenarios increases. Similarly, a comparison of expected wage dynamics before and after the age of 40 displayed in table A3, reveals that the coefficient on the degree signal decreases with experience at later stages of career, while the one on productivity, stays almost constant with increasing experience. This pattern has been found repeatedly in actual wage data (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange and Topel, 2006). It suggests that the relative importance of easily observable characteristics (like a degree) decreases with experience while that of employee productivity becomes relatively more important over the working life. Third, as regards relative wage dynamics over time, figure 4 unveils a lot of growth after graduating at first, i.e., when productivity is not fully revealed yet. Large perceived initial returns to experience among university graduates lead to rapidly increasing gaps between scenarios in the beginning, which then only partly close at later stages when productivity becomes relatively more important than the degree. Moreover, when including an interaction term between productivity and the signal in the estimations of table A3, we find that perceived productivity and degree completion are complements when it comes to wage returns. That is, high productivity individuals seem to expect larger returns to experience after graduation, possibly because the jobs they expect to pursue with a degree require tasks that more closely match their abilities.

There are several potential reasons for the low support for diminishing initial graduation premia. One explanation is that graduating not only leads to higher perceived lifetime returns through increased starting wages, but that it also helps job beginners to get into different kinds of jobs compared to university leavers. Moreover, they may believe that initial assignment to a high-earning job allows individuals to acquire specific human capital.[21] These jobs might then have stronger potential for wage increases over time. Nonetheless, we need to recall that both our main results and figure 4 (as well as Appendix figure A3) only refer to master students who already have a university degree even in the scenario of quitting their current studies. Hence, it is not quite straightforward to expect that students with only a bachelor degree perform substantially different jobs compared to master students. Although the mechanisms behind this result are not completely evident, we can conclude that the initial expected graduation premium caused by the signaling value is not only lasting but even growing over time and that it outweighs perceived employer learning in the long run.

[21]The same effect could arise from productivity spillovers from high-performing co-workers or if the signal grants advantages in promotions, e.g., because early earnings are a signal for later earnings (see, e.g., Waldman, 2016).

Figure 4: Expected yearly wages over the life time by perceived productivity



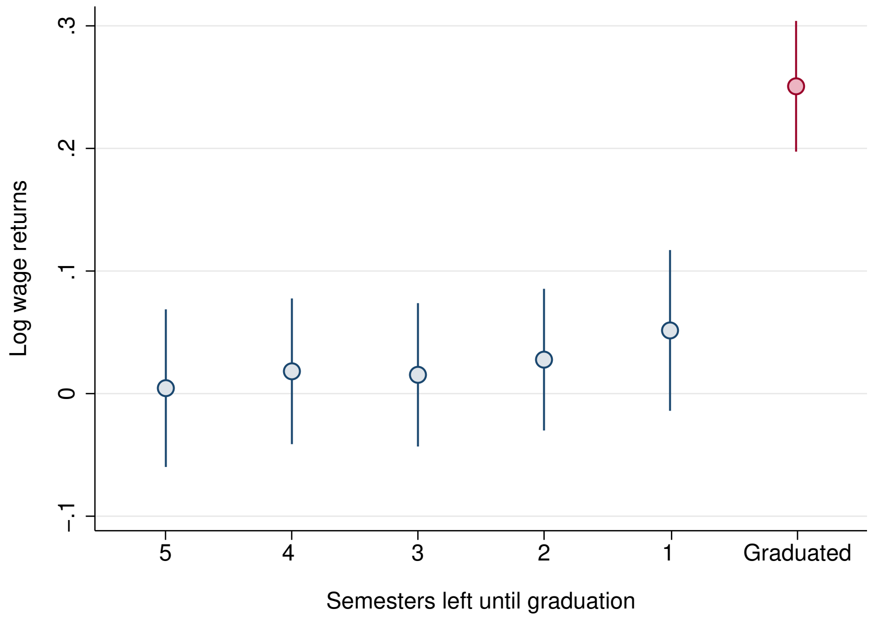
Notes: Figure 4 shows the development of expected yearly wages over for master students who do not plan to work in a legally-licensed occupation. The red lines correspond to graduating, and the blue lines to leaving university without a degree. The darker (top) lines of each color correspond to the upper 50% of the perceived work ability distribution and the lighter (bottom) lines correspond to the bottom 50% of the perceived work ability distribution. Colored areas indicate the 95% confidence intervals.

4.4 Robustness checks

In this subsection, we assess the robustness of our results. For this purpose, we first relax the linearity and homogeneity assumptions that we made to estimate the human capital effect. We then study potential biases that may arise from dynamic selection related to student dropout over time. Finally, we assess the sensitivity of our results with respect to sample selection.

Linearity of human capital accumulation First, we assume that the human capital effect is linear in semesters. This is a reasonable assumption as credit points at university normally build up linearly with an increasing number of semesters completed. However, from an individual perspective this does not always hold true. Besides, some courses or activities might be perceived as creating more human capital than others. Therefore, we estimate an alternative fixed effects specification easing the assumption that human capital accumulation is a linear process by looking at the effect of each semester separately. Equation (6) shows the respective specification:

Figure 5: Plotted coefficients of fixed effect model with semester dummies



Notes: Figure 5 displays the coefficients and 95% confidence intervals from estimating equation (6), where the blue dots correspond to β_n and the red dot to β_1. The baseline is having six or more semesters until graduation. The regression only includes master students who have a maximum of eight semesters left to study.

$$W_i^c = \beta_0 + \beta_1 degree_i^c + \beta_n \mathbb{1}_{n,i}^c + \gamma_i + \epsilon_i, \tag{6}$$

where $\mathbb{1}_{n,i}^c$ is an indicator function representing a set of dummy variables for the number of semesters n that individual i still needs to study. The baseline is having 6, 7 or 8 semesters more to study, as we bundled the "high semester" students in one category due to the small number of observations.

Figure 5 visualizes the results of the fixed effects model with semester dummies and displays the estimated coefficients with 95% confidence intervals.[22] The coefficients indicate how expected starting wages after leaving change compared to the baseline of having 6 to 8 semesters left to study. It seems that the development over semesters is slightly increasing, although in line with the model estimated in section 4.2 none of the coefficients are significantly different from zero and we do not see any non-linearities. The graph shows that graduating with a master degree causes a considerable jump in expected wages of 25.1% compared to the baseline, which is in line with the estimated effect of a degree of 20.6% in our main model

[22]See appendix table A4 for the regression results.

specification. As before, this is a substantially stronger effect compared to the value of an additional semester studied.

Increasing human capital by semesters A second assumption, that we make to approximate the human capital effect, is that with fewer semesters left to study the human capital value should increase. Although this is straightforward at an individual level, it might not always hold true when comparing between individuals, because students who have the same number of semesters left to study are not necessarily at the exact same stage of their studies. We test this assumption by restricting the sample to students who are studying in regular study time, meaning that the sum of semesters left to study and semesters already studied cannot exceed the regular study time plus one. Fixing the sum of these two variables ensures strong comparability of semesters between students as they are all participating in a master's program that they are about to finish in regular study time. In table 4, columns 1 to 3, we show that the estimated effect of obtaining a degree slightly decreases but remains at a significant 18.7% wage increase (compared to 20.6%). The estimated human capital effect remains statistically insignificant. Overall, our estimation of the signaling effect is robust to this subsample analysis.

Dynamic selection Third, so far we have abstracted from dynamic selection. Although we have students at all study stages in our sample, the students in the later semesters of their studies might be a selected sample as they have already reached a later stage of studying. At the same time, students with a higher expected graduation premium might be less likely to leave university than students with lower expected returns of graduating, in which case we might overestimate the signaling value due to dynamic selection. To test whether our results are affected by dynamic selection, we estimate the signaling effect only for students who finished high school with an average grade in the top third of our sample. According to Isphording and Wozny (2018), a better high-school grade is highly predictive of graduating within Germany. Hence, if we restrict our analysis to the top performers in high school, this should reduce potential dynamic selection, while also improving comparability between students across different study stages. Columns 4 to 6 of table 4 present the estimates for this sample. We observe a signaling effect of roughly 18%, which is close to the results in our main analysis. The human capital effect turns statistically significant and increases slightly compared to our main analysis, indicating that high performers benefit relatively more from education as regards their human

Table 4: Robustness checks

	Regular study time			Best third in high-school			Max 12 semesters		
	(1) Starting wage levels	(2) Starting wage logs	(3) Starting wage logs	(4) Starting wage levels	(5) Starting wage logs	(6) Starting wage logs	(7) Starting wage levels	(8) Starting wage logs	(9) Starting wage logs
Semesters	124.398	0.012	0.012	493.765*	0.015**	0.014**	180.957	0.006	0.005
	(298.834)	(0.008)	(0.008)	(253.070)	(0.007)	(0.007)	(133.325)	(0.004)	(0.004)
Degree	7,229.140***	0.191***	0.188***	5,924.103***	0.180***	0.189***	7,191.741***	0.212***	0.205***
	(988.126)	(0.025)	(0.025)	(828.544)	(0.024)	(0.024)	(493.595)	(0.014)	(0.014)
Interaction effects:									
Licence*Degree			0.010			0.001			0.032**
			(0.021)			(0.026)			(0.016)
Civil servant*Degree			0.006			-0.054*			0.007
			(0.024)			(0.030)			(0.018)
Constant	30,675.476***	10.312***	10.312***	32,090.417***	10.322***	10.321***	30,530.587***	10.283***	10.284***
	(947.072)	(0.024)	(0.024)	(810.200)	(0.023)	(0.023)	(463.361)	(0.013)	(0.013)
N	1376	1376	1372	1046	1046	1042	2822	2822	2812
adj. R^2	0.455	0.522	0.522	0.436	0.499	0.501	0.459	0.503	0.504

Notes: Table 4 shows the outcomes of the robustness analysis. Columns 1-3 comprise students who are expected to finish within regular study time, i.e., four semesters in total. Columns 4-6 include every student who had a high-school GPA in the highest 33%. Column 7-9 includes all students who are in the 12th semester or less. The sample only includes master students. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

capital accumulation. However, with a 1.5% wage return per semester it remains considerably lower than the effect of the degree.

Sensitivity with respect to sample selection Finally, in our main analysis we restrict the sample to students who indicate having at most eight semesters left to study.[23] To test the sensitivity of our findings with respect to the exact thresholds of semesters, columns 7 to 9 in table 4 in the appendix show the results for a sample including students who report having up to 12 semesters left to study (capturing more than 99% of all students). The results show that the magnitude of the graduation premium is robust to expanding the sample to these students.

Overall, we can conclude that for master students the expected signaling effect is substantial and robust across all specifications. Throughout, the human capital value remains positive but small. Moreover, the relative importance of human capital to the signaling effect remains minor. For bachelor students, we repeat all robustness checks and find that the signaling value also remains robust across specifications (see table A5 in the appendix).

5 Implications of the signaling theory

The previous sections have shown that students predominantly believe that the signaling value is responsible for the largest part of the returns to graduating. A natural next step is to check whether further implications of the signaling theory also hold in our sample. Regarding our analysis, there are two testable implications of Spence's signaling theory. First, as the degree is assumed to be the only way to signal productivity in the labor market, the short-term returns should be the same for everyone who obtained the signal, independent of unobservable skills or background characteristics. Second, as the immediate returns from graduating should not differ between individuals, the decision to leave university should be mostly driven by the (psychic) cost of education, rather than the potential earnings after finishing.

5.1 Heterogeneities in signaling

A key assumption of the signaling model is that an individual's productivity type is not directly observable and that employers therefore use the signal to infer an individual's productivity. If a degree is no more than a way of signaling (future)

[23] As the regular study time for master students is four semester in Germany, we restricted the sample to double the regular amount of time needed for studying.

productivity, then the expected returns should ideally apply to everybody who obtains that signal, and the signaling value should not vary between individuals with the same observable (but different unobservable) characteristics.

However, Spence's signaling theory does not account for labor market discrimination. Some background characteristics are usually observable in the application process and labor market discrimination with respect to wage or other labor market outcomes is a widely-documented phenomenon in Western labor markets. Hence, one could expect to observe heterogeneities in the signaling value concerning characteristics that are subject to discrimination, such as gender (see Belman and Heywood, 1991, for earlier evidence on heterogeneities in signaling values for women and minorities).

Moreover, the model of Spence abstracted from the fact that various educational degrees exist, e.g., graduating from different fields or majors. These degrees can be interpreted as distinct signals, which are valued differently in the labor market. Hereby, each type of degree may signal different underlying unobservable characteristics, such as stamina, on-the-job productivity, or creativity.

To test whether there are heterogeneous signaling values, we include interaction terms between the degree dummy and various background variables in our fixed effects model. We estimate the following equation:

$$W_i^c = \beta_0 + \beta_1 degree_i^c + \beta_2 semesters_i^c + \beta_3 (degree_i^c * X_i) + \gamma_i + \epsilon_i, \tag{7}$$

where X_i is a set of background characteristics comprising gender, socioeconomic background, study characteristics and perceived relative job ability, to test whether these characteristics matter for the value of the degree signal in the labor market.

Table 5 displays the regression results. Overall, it seems that the expected returns from the degree do not strongly depend on individual skills or background characteristics, with two main exceptions: gender and major. The interaction term with the gender dummy shows a statistically significant positive effect for males, where the expected signaling value is roughly three percentage points higher for males than for females when controlling for major and other background characteristics (see column 5). The existence of gender discrimination in the labor market is an intuitive explanation for this finding. In addition, the interaction terms with the major categories (humanities/social sciences, medicine, STEM, law and economics/business) are statistically significant. With the humanities/social sciences major as a baseline, we observe a higher signaling value for medicine and STEM majors. As explained before, this result is reasonable as graduating in a different major can be interpreted as acquiring a different signal.

Table 5: Wage returns - heterogeneities

	Starting wage (logs)				
	(1)	(2)	(3)	(4)	(5)
Semesters	0.006	0.006	0.007	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Degree	0.188***	0.204***	0.202***	0.219***	0.204***
	(0.016)	(0.017)	(0.017)	(0.045)	(0.045)
Interaction effects:					
Sex*Degree	0.044***				0.029**
	(0.013)				(0.013)
Academic*Degree		-0.007			-0.006
		(0.012)			(0.012)
Migrat*Degree		0.029			0.028
		(0.018)			(0.018)
Perc. job ability*Degree			0.001		-0.001
			(0.012)		(0.012)
Gpa*Degree				-0.008	-0.007
				(0.006)	(0.006)
Majors:					
Medicine*Degree				0.075**	0.077**
				(0.031)	(0.031)
STEM*Degree				0.084***	0.076***
				(0.017)	(0.018)
Law*Degree				0.030	0.028
				(0.069)	(0.067)
Economics*Degree				0.019	0.014
				(0.016)	(0.016)
Constant	10.286***	10.286***	10.288***	10.283***	10.281***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
N	2754	2754	2754	2754	2754
adj. R^2	0.511	0.508	0.507	0.520	0.522

Notes: Table 5 includes several interaction terms between the degree premium and background characteristics. The sample only includes master students who have a maximum of eight semesters left until they reach their degree. The regressions are controlled for licensing effects. The baseline subject is humanities. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

At the same time, we do not see any significant heterogeneity based on socioeconomic background, perceived job ability or GPA. Regarding GPA, it is surprising that grades do not seem to play a role for the valuation of the signal, as a high GPA could function as an additional signal in the labor market. However, grades may often be specific to the university, the study program or the federal state in which the degree was obtained and hence might be difficult for employers to evaluate. Further on, grades reflect *academic* ability, which is assumed to be correlated to job ability but is not necessarily similar to work productivity, which could also explain that the GPA does not seem to function as an additional signal.

In addition, the two characteristics associated with socioeconomic status – i.e. the indicators for migration background and having at least one parent with an academic degree – do not appear to affect the value of the signal. As especially parents' educational background is unobserved by potential employers, the lack of a significant interaction term is suggestive evidence of the signaling theory, which states that the signal should be independent of unobservable characteristics. The same holds true for perceived work ability. Table 5 indeed presents evidence that the perceived work ability of students has no effect on the value of the expected signal. At the same time, section 4.3 shows that students expect their work ability to yield wage returns in the long run. Therefore, the fact that the perceived job ability does not have an effect on the *immediate* returns of graduation further supports the signaling interpretation.[24]

5.2 Determinants of leaving

The second implication from the signaling theory relates to students' decision whether or not to complete tertiary education. As the returns from graduating should not substantially differ between individuals sending the same signal, the decision to select out of education should be driven by the (psychic) cost of education only, and not by the potential earnings gain from finishing. Besides testing this implication of Spence's theory in our data, the following analysis is also informative about the determinants of student dropout. This is a relevant issue as our previous analysis has shown that the largest part of the return to studying is associated with graduating, and hence leaving university earlier is very costly. Nonetheless, 11% of all master

[24]In appendix table A6, we show the same results for bachelor students. The findings with respect to gender and majors are similar to those for master students. We discuss this finding in detail in appendix section E.

students in Germany leave university without a degree (Heublein and Schmelzer, 2014).[25]

To test the second hypothesis, we regress the perceived probability of leaving university without a degree on the immediate wage and non-wage returns to graduating, study performance and satisfaction, and background characteristics. For the wage returns, we compute the absolute difference of expected entry wages between the graduation and leaving scenarios. For the non-wage returns, we use standardized differences of expected immediate returns between scenarios. The results are presented in table 6. In columns 1 and 2, we include both wage and non-wage returns and test whether the returns from graduating predict expected leaving probabilities. As we know that the signaling value depends on the chosen major, we additionally control for majors in column 2 to test whether the probability to leave is affected by major-specific wage returns. The table shows that expected wage returns do not seem to affect students' leaving probability. This finding is in line with the hypothesis that wage returns should not matter for deciding whether to obtain the signal, as the returns are the same for everybody who acquires it. For non-wage returns, it is less clear what to expect, as they might not be perfectly correlated with wage returns and – unlike wage returns – they may differ between individuals with the same type of degree. We indeed see that increased job satisfaction and job-finding probability returns reduce the probability of leaving.

Concentrating on the cost-related variables included in column 3, we find additional support for the second hypothesis. Study satisfaction – which is an indicator of the current consumption utility of studying and a proxy of psychic costs – is strongly associated with the probability of leaving university. Being satisfied instead of dissatisfied with one's studies reduces the leaving probability by over five percentage points. Further, we include ability measures that can be thought of as being related to effort costs, as a lower academic ability may make studying more difficult. Accordingly, we find that having a higher study GPA reduces the leaving probability.

Taken together, we find support for the second testable implication of the signaling theory. Students seem to mainly base their decision whether or not to leave university at an early stage on cost-related factors, while wage returns are not predictive for leaving.

[25]For bachelor students, the observed dropout rate is 28%. These data were collected in Germany and refer to the student cohort graduating in 2012.

Table 6: Regression results for probability to leave

	Leaving probability		
	(1)	(2)	(3)
Wage returns (in 1,000 Euro)	-0.025	-0.022	-0.051
	(0.055)	(0.057)	(0.055)
Job satisfaction return	-1.333***	-1.431***	-1.425***
	(0.497)	(0.506)	(0.496)
Job finding prob. return	-1.708***	-1.679***	-1.494***
	(0.576)	(0.571)	(0.569)
Satisfied with studies			-5.345***
			(1.347)
Male			1.017
			(0.897)
Academic parent(s)			0.110
			(0.897)
Migration background			2.254
			(1.488)
Study GPA			-1.366***
			(0.408)
High-school GPA			0.215
			(0.284)
Perceived academic ability			-0.027
			(0.027)
Constant	7.452***	9.150***	22.895***
	(0.677)	(2.437)	(4.059)
N	1381	1381	1381
adj. R^2	0.012	0.012	0.041
Controlled for major	No	Yes	Yes
Mean leaving probability	7.75	7.75	7.75

Notes: Table 6 regresses the probability of leaving on the expected returns from graduating and several background characteristics. For the wage returns, we computed the absolute difference of expected labor market entry wages between the graduation and leaving scenario. For non-wage returns, we used standardized differences of expected immediate returns between scenarios. The sample only includes master students who have a maximum of eight semesters left until they reach their degree. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

6 Conclusion

While substantial returns to university education have been documented in a large body of empirical literature, the extent to which these returns reflect the signaling rather than the productivity-enhancing human capital effect of education remains open to debate. Based on novel data with measures of counterfactual labor market outcomes for graduating and leaving university without a degree, this paper documents large perceived returns to degree completion. Moreover, estimates from within-person fixed effects models unveil substantial signaling effects of around 20% in terms of starting wages for a master degree, exceeding the human capital effect of education by 3-5 times over the course of studies. Degree effects are persistent in absolute terms, but become less important relative to expected on-the-job productivity in explaining expected wage dynamics over the course of career.

Although in terms of methodology our approach differs from the existing literature, our findings are complementary. First, we provide novel evidence that among current students *perceived* signaling tends be important and highly persistent in terms of lifetime wages. Second, our findings are in line with two predictions from the signaling theory: (i) heterogeneities in perceived signaling – albeit for different fields of study – are relatively unimportant when compared to the overall effect of obtaining a degree, and (ii) when compared to the psychic cost of studying, the graduation premium matters little for the perceived probability of leaving university without a (further) degree. Third, using within-individual variation and information on students' grades we can largely dismiss an alternative (selection) hypothesis that dates back to Chiswick (1973) (see also Lange and Topel (2006)), stating that the graduation premium arises because graduates are disproportionately comprised of individuals whose returns to education are particularly large. If this hypothesis held true, it would be unlikely to observe homogeneously high within-individual returns to degree completion.

Our results hold implications for both understanding students' motivations to study and for economic policy. First, given their expectation of substantive signaling effects, students' main motivation to attend higher educational institutions seems to be to obtain credentials rather than to learn new skills, concepts, and material. Thus, in light of our findings, common complaints among professors regarding their students' limited willingness to study material beyond what is on the exam seem warranted. Moreover, our findings provide a rationale for the sustained demand for enrollment in selective educational institutions, even though many studies find no benefits in terms of learning achievements or actual wages (see, e.g., Dale and

Krueger, 2002). In terms of policy, the fact that most of the perceived returns to education are private implies that tuition fees should have little effect on student enrollment. Thus, our findings may explain why a temporary introduction of tuition fees in Germany – although contested politically – had only small effects on study take-up (Hübner, 2012). Finally, the finding that perceived returns are unable to predict perceived university-leaving probabilities suggests that policies to fight student dropout should focus on measures that target the psychic costs of studying rather than the perception of future returns for instance.

The paper also opens up several avenues for future research. First, our results only hold for individuals who are currently enrolled at a university or college of applied sciences. In this sense, it would be valuable to extend the analysis to high-school students, e.g., to study the effect of the perceived graduation premium for the extensive margin of student enrollment. Second, it would be informative to investigate whether the labor demand side (e.g., human resource managers) holds similar perceptions regarding the relative importance of signaling and human capital values and how perceptions on either side translate into equilibrium wage outcomes.

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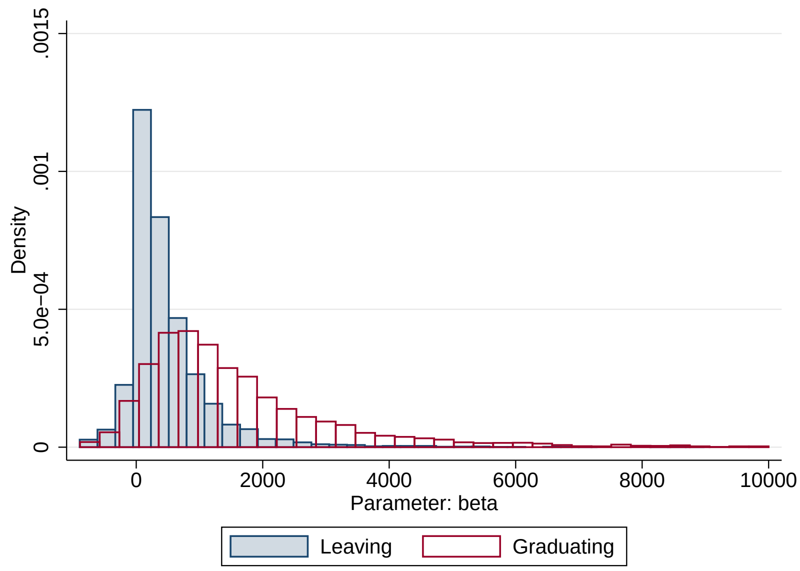
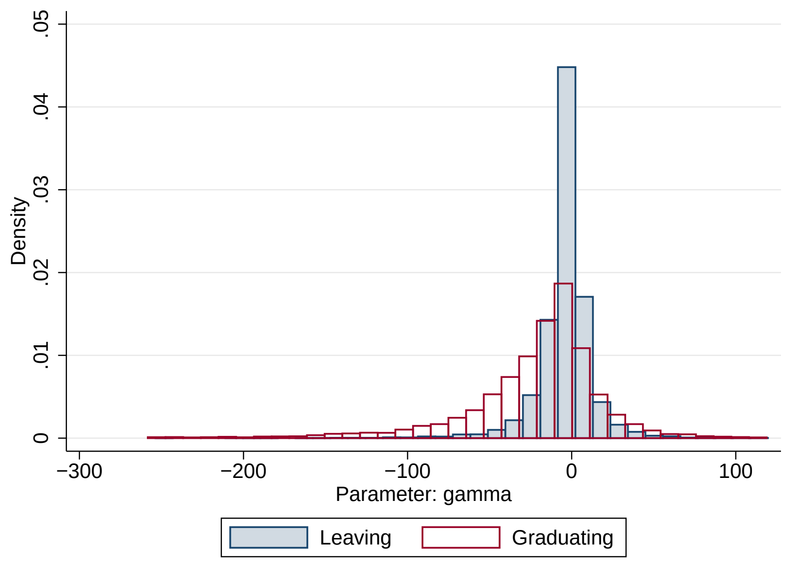
Appendix

A Additional figures and tables

Figure A1: Computed parameters of the mincer wage equation by scenario



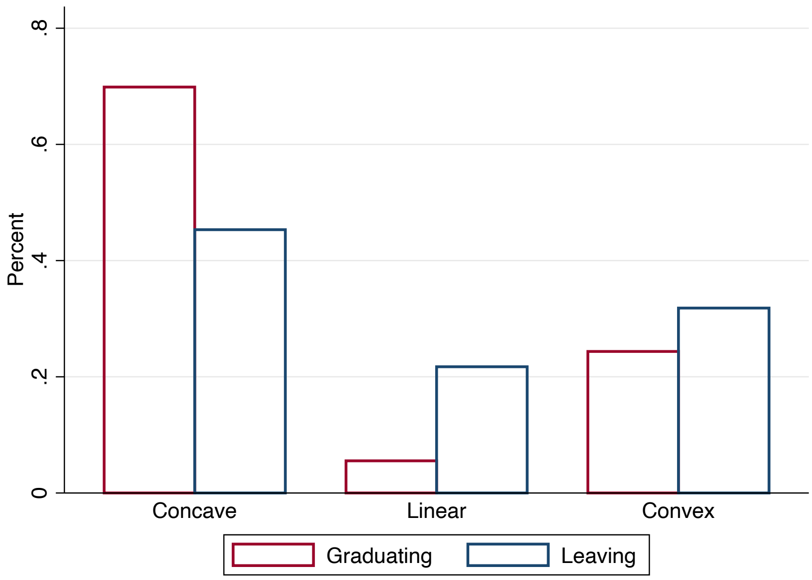
(a) Density of slope parameter β



(b) Density of curvature parameter γ

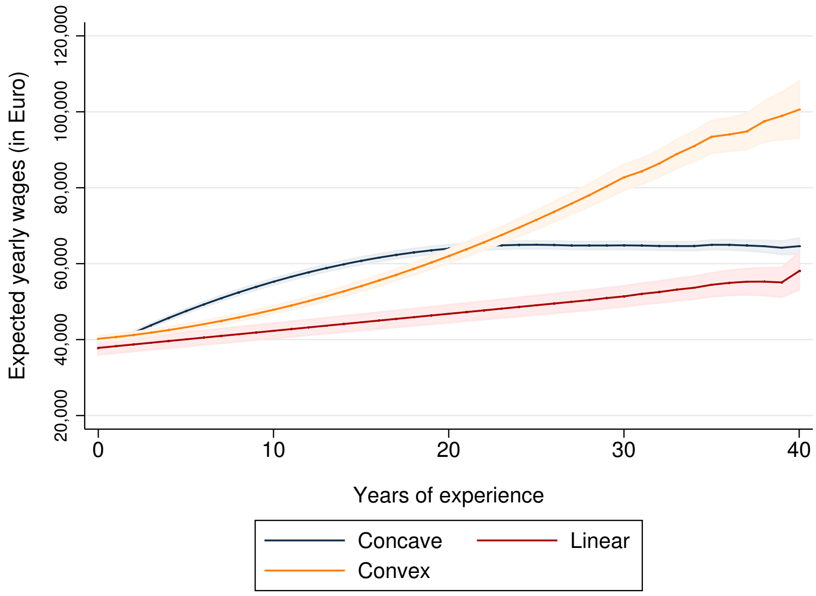
Notes: Figure A1 panel A shows the distribution of the computed slope parameter β from equation (1). Panel B shows the respective curvature parameter γ of equation (1). Both graphs only display parameters that lie between the 1st and the 99th percentile of the distribution of graduating parameters.

Figure A2: Patters of wage trajectories

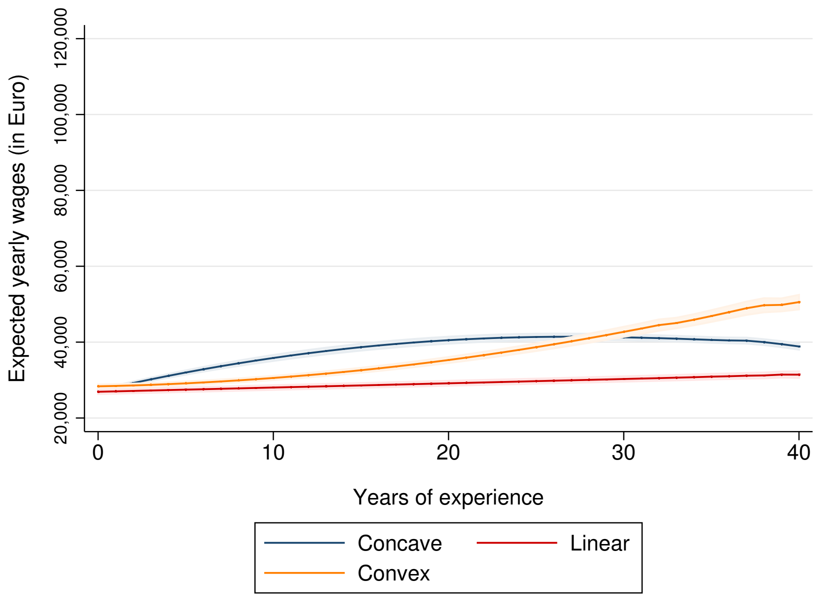


Notes: Figure A2 shows the share of different wage trajectory patterns, that were classified on hands of the parameters of the mincer equation (see equation 1) by scenario.

Figure A3: Expected wage trajectories by scenario and type



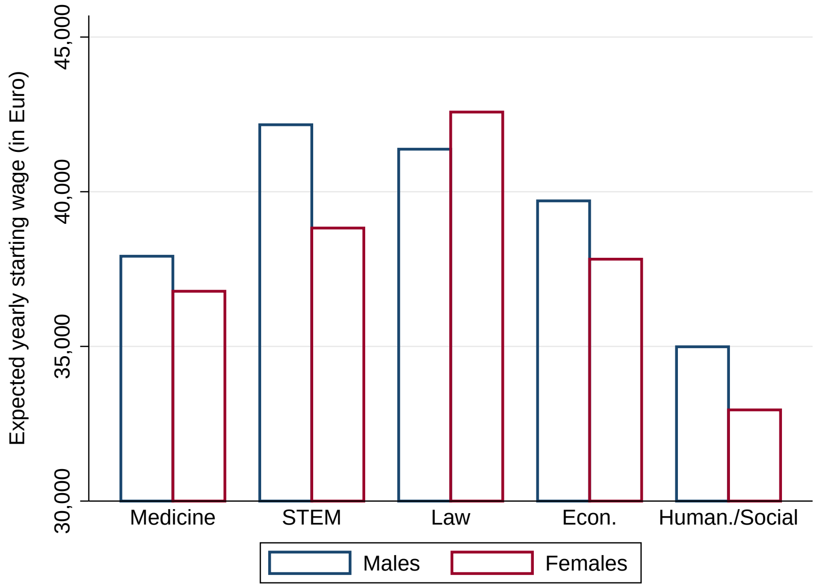
(a) Average wage after graduation, by wage function classification



(b) Average wage after leaving, by wage function classification

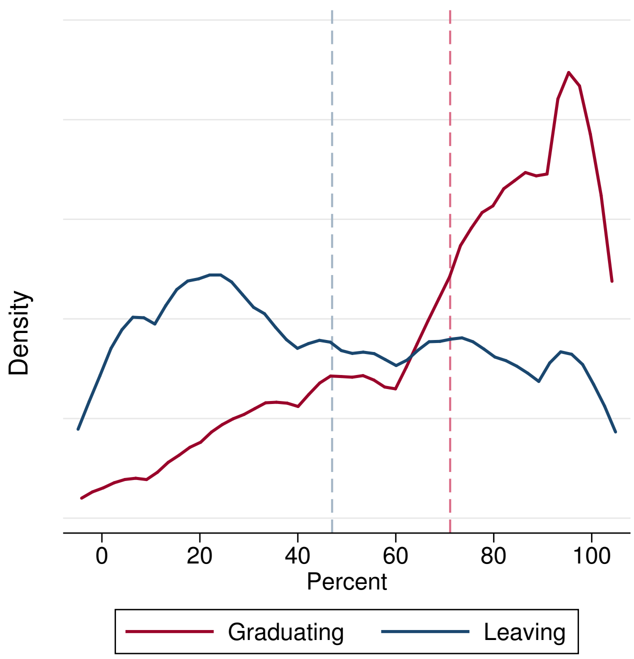
Notes: Figure A3 shows the expected wage trajectories by different wage function classifications. Panel A shows the wage trajectories for the scenario of graduating and panel B for the scenario of leaving university. The wage trajectories are classified in terms of different parameters of equation (1).

Figure A4: Expected yearly earnings after graduating at labor market entry by gender and major



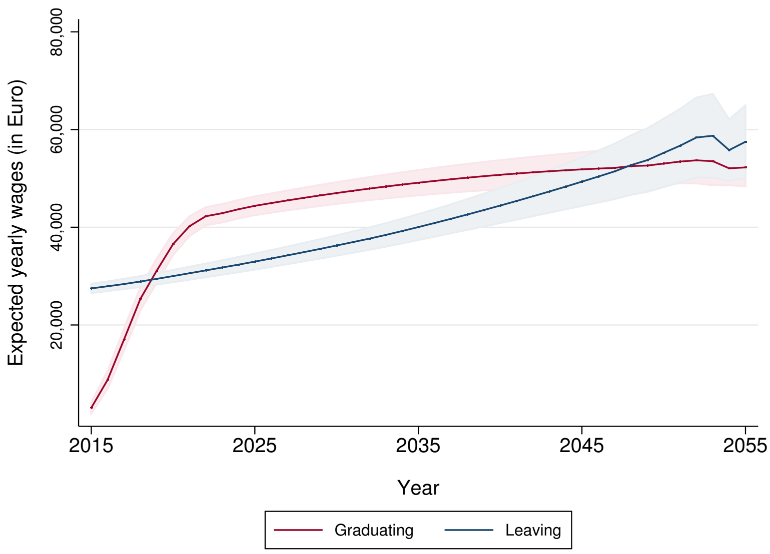
Notes: Figure A4 displays the average expected yearly starting wage after graduating university by gender and major. The sample includes both bachelor and master students.

Figure A5: Expected probability to find a suitable job at labor market entry by scenario



Notes: Figure A5 displays the density of the expected probability to find a suitable job at labor market entry for both scenarios. The average expected job-finding probability at labor market entry for graduating is 71.1% and for leaving university without a degree 47.0%. The sample includes both bachelor and master students.

Figure A6: Expected yearly wage over the life time



Notes: Figure A6 shows the development of the expected yearly wage over the life time for students who expect to diminish the wage difference between the graduating and leaving scenario. The colored areas around the lines indicate the 95% confidence intervals.

Table A1: Wage returns (bachelor students)

	(1) Starting wage levels	(2) Starting wage logs	(3) Starting wage logs
Semesters	253.067***	0.006***	0.006***
	(92.238)	(0.002)	(0.002)
Degree	10,491.155***	0.326***	0.321***
	(405.822)	(0.010)	(0.011)
Interaction effects:			
Licence*Degree			0.035***
			(0.010)
Civil servant*Degree			-0.026**
			(0.012)
Constant	27,991.612***	10.173***	10.175***
	(396.736)	(0.010)	(0.010)
N	8768	8768	8730
adj. R^2	0.486	0.598	0.600

Notes: Column 1 in table A1 shows the effects on the level of yearly starting wages, while the dependent variable in columns 2 and 3 are log starting wages. The sample only includes bachelor students, who have maximum of eight semesters left until they reach their degree. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A2: Non-wage returns (bachelor students)

	(1) Satisfaction	(2) Satisfaction	(3) Job finding probability	(4) Job finding probability
Semesters	0.007	0.008	0.009	0.010
	(0.013)	(0.013)	(0.009)	(0.009)
Degree	1.484***	1.464***	0.815***	0.776***
	(0.060)	(0.062)	(0.042)	(0.043)
Interaction effects:				
Licence*Degree		0.176***		0.239***
		(0.061)		(0.042)
Civil servant*Degree		-0.163**		-0.130***
		(0.068)		(0.050)
Constant	0.030	0.037	0.038	0.044
	(0.057)	(0.057)	(0.040)	(0.040)
N	8768	8730	8768	8730
adj. R^2	0.461	0.462	0.347	0.353

Notes: Columns 1 and 2 in table A2 show the effects on expected job satisfaction at labor market entry, while the dependent variable in columns 3 and 4 is the expected probability to find a suitable job. Both satisfaction and job-finding probability are expressed in standard deviations according to equation (5). The sample only includes bachelor students who have at most eight semesters left until they reach their degree. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Employer learning by work experience

	Starting age & age 40		Age 40 & age 55	
	(1)	(2)	(3)	(4)
	Log Wages	Log Wages	Log Wages	Log Wages
Semesters	0.012**	0.012**	-0.002	-0.002
until next Degree	(0.005)	(0.005)	(0.007)	(0.007)
Signaling	0.203***	0.186***	0.337***	0.313***
(Graduated)	(0.016)	(0.019)	(0.025)	(0.027)
Work	0.016***	0.015***	0.011***	0.011***
Experience (years)	(0.001)	(0.001)	(0.001)	(0.001)
Interaction Effects:				
Semester*Experience	0.000	0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Signal*Experience	0.008***	0.008***	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Productivity*Experience	0.003***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Productivity*Signal		0.027**		0.038**
		(0.013)		(0.016)
Constant	10.304***	10.305***	10.369***	10.371***
	(0.016)	(0.016)	(0.024)	(0.023)
N	5524	5524	5524	5524
adj. R^2	0.579	0.580	0.568	0.569

Notes: Table A3 shows the effects of semesters studied, the degree and work experience on expected log wages for both scenarios of graduating and leaving university. Column 1 and 2 include wage expectations for the points in time when participants would start a job and at age 40. Column 3 and 4 include wage expectations for the points in time where participants would be 40 and 55 years old. The sample only includes master students who have maximum of eight semesters left until reaching their degree. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Robustness analyses - wage returns with semester dummies (master students)

	Immediate returns
5 Semes. until degree	0.004
	(0.033)
4 Semes. until next degree	0.018
	(0.030)
3 Semes. until next degree	0.015
	(0.030)
2 Semes. until next degree	0.028
	(0.029)
1 Semes. until degree	0.052
	(0.033)
Degree	0.251***
	(0.027)
N	2762
adj. R^2	0.506

Notes: Table A4 displays the coefficients from estimating equation (6). The regression only includes master students who have at most eight semesters left to study. The baseline is to have six or more semesters until graduation. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A5: Robustness analyses (bachelor students)

	Regular study time			Best third in high-school			Max 12 semesters		
	(1) Starting wage levels	(2) Starting wage logs	(3) Starting wage logs	(4) Starting wage levels	(5) Starting wage logs	(6) Starting wage logs	(7) Starting wage levels	(8) Starting wage logs	(9) Starting wage logs
Semesters	90.060	0.008	0.008	62.166	-0.001	-0.000	70.804	0.002	0.002
	(244.628)	(0.006)	(0.006)	(163.854)	(0.004)	(0.004)	(68.489)	(0.002)	(0.002)
Degree	10,884.868***	0.312***	0.304***	11,374.875***	0.362***	0.352***	11,166.608***	0.341***	0.336***
	(932.567)	(0.023)	(0.023)	(749.475)	(0.019)	(0.019)	(348.585)	(0.009)	(0.009)
Interaction effects:									
Licence*Degree			0.060***			0.040**			0.034***
			(0.020)			(0.018)			(0.010)
Civil servant*Degree			-0.032			-0.009			-0.024**
			(0.024)			(0.023)			(0.012)
Constant	27,121.896***	10.174***	10.176***	26,977.514***	10.135***	10.137***	27,148.962***	10.154***	10.156***
	(921.197)	(0.022)	(0.022)	(726.193)	(0.018)	(0.018)	(330.106)	(0.008)	(0.008)
N	2622	2622	2610	2842	2842	2828	9588	9588	9548
adj. R^2	0.452	0.566	0.569	0.488	0.600	0.601	0.483	0.596	0.597

Notes: Table A5 shows the outcomes of the robustness analysis. Columns 1-3 include students who are expected to finish within regular study time, i.e. four semesters in total. Columns 4-6 include every student who had a high-school GPA in the highest 33%. Column 7-9 includes all students who are in the 12th semester or less. The sample only includes bachelor students. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A6: Wage returns (bachelor students) - heterogeneities

	Starting wage (logs)				
	(1)	(2)	(3)	(4)	(5)
Semesters	0.006***	0.006***	0.007***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Degree	0.288***	0.306***	0.309***	0.246***	0.206***
	(0.011)	(0.011)	(0.012)	(0.022)	(0.022)
Interaction effects:					
Sex*Degree	0.072***				0.040***
	(0.009)				(0.009)
Academic*Signal		0.015*			0.019**
		(0.009)			(0.009)
Migrat*Degree		0.051***			0.041***
		(0.012)			(0.012)
Perc. job ability*Degree			0.021**		0.015*
			(0.009)		(0.009)
Gpa*Degree				-0.004	-0.003
				(0.003)	(0.003)
Majors:					
Medicine*Degree				0.080***	0.083***
				(0.020)	(0.020)
STEM*Degree				0.160***	0.146***
				(0.012)	(0.012)
Law*Degree				0.168***	0.165***
				(0.045)	(0.045)
Economics*Degree				0.104***	0.096***
				(0.011)	(0.012)
Constant	10.174***	10.175***	10.176***	10.172***	10.172***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
N	8730	8730	8730	8730	8730
adj. R^2	0.606	0.602	0.600	0.619	0.623

Notes: Table A6 includes several interaction terms between the degree premium and background characteristics. The sample only includes bachelor students who have a maximum of eight semesters left until they reach their degree. The regressions are controlled for licensing effects. The baseline subject is humanities. Standard errors are in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

B Counterfactual labor market questions

How do you expect your future workday when you finish your first choice [...]? Estimate the following variables for the different stages of life.

	Working hours/Week	Salary/Year (gross in €)
at career start	[ ]	[ ]
at age 40	[ ]	[ ]
at age 55	[ ]	[ ]

(Original: *Wie erwarten Sie Ihren zukünftigen Arbeitsalltag, wenn Sie ihre erste Wahl [...] zu Ende studieren? Schätzen Sie die folgenden Variablen jeweils für die verschiedenen Lebensabschnitte.*)

How do you expect your future workday when you cannot complete a degree and start working without a degree? Estimate the following variables for the different stages of life.

	Working hours/Week	Salary/Year (gross in €)
at career start	[ ]	[ ]
at age 40	[ ]	[ ]
at age 55	[ ]	[ ]

(Original: *Wie erwarten Sie Ihren zukünftigen Arbeitsalltag, wenn Sie kein Studium abschließen können und ohne Studienabschluss beginnen zu arbeiten? Schätzen Sie die folgenden Variablen jeweils für die verschiedenen Lebensabschnitte.*)

How do you rate the likelihood of not finding a suitable job for the various scenarios at the time of starting your career?

Completion first choice [...]	[ ]
Dropout - no degree	[ ]

(Original: *Wie schätzen Sie die Wahrscheinlichkeit zum Zeitpunkt des Berufseinstiegs keinen passenden Job zu finden für die verschiedenen Szenarien ein?*)

How do you rate the likelihood of not finding a suitable job for the various scenarios at age 40?

Completion first choice [...]	[ ]
Dropout - no degree	[ ]

(Original: *Wie schätzen Sie die Wahrscheinlichkeit mit 40 Jahren keinen passenden Job zu finden für die verschiedenen Szenarien ein?*)

How do you rate your professional satisfaction at the time you started your career for the various scenarios?
1 → very dissatisfied, 10 → very satisfied

	1	2	3	4	5	6	7	8	9	10
Completion first choice [...]	○	○	○	○	○	○	○	○	○	○
Dropout - no degree	○	○	○	○	○	○	○	○	○	○

(Original: *Wie schätzen Sie Ihre berufliche Zufriedenheit zum Zeitpunkt des Berufseinstiegs für die verschiedenen Szenarien ein?*)

How do you rate your professional satisfaction at age 40 for the various scenarios?
1 → very dissatisfied, 10 → very satisfied

	1	2	3	4	5	6	7	8	9	10
Completion first choice [...]	○	○	○	○	○	○	○	○	○	○
Dropout - no degree	○	○	○	○	○	○	○	○	○	○

(Original: *Wie schätzen Sie Ihre berufliche Zufriedenheit mit 40 Jahren für die verschiedenen Szenarien ein?*)

C Data-cleaning rules

For our analysis, it was important that all included individuals filled in the following variables: expected labor market outcomes for the leaving and finishing scenarios at all points in time, probability of leaving, probability to change majors, gender, age, degree enrolled in, semesters done, semesters left until next degree, perceived academic ability, perceived job ability, GPA, high-school GPA, study costs, study satisfaction, university major, academic parents, and migration background. If one of these were missing, we excluded the individual from our sample.

As individuals could fill in any expected wage and working hours, we cleaned them to remove implausible values. With respect to working hours, this means that we exclude values above 168 hours, as this is the maximum amount of hours within a week (amounts to less than 0.05% of our sample). For wages, we first calculated the wage per hour by dividing the yearly wage by 52 and the indicated working hours per week. We then exclude everybody who has a hourly wage of below €7.50, which is even lower than the minimum wage of €8.50 that was introduced in Germany at the beginning of 2015. In addition, we exclude people who have an hourly wage above €80 at labor market entry or above €240 at age 40 and 55. For the remaining sample, we multiply the hourly wage by 2080 to obtain yearly full-time wage expectations.

D Negative signaling

In this paper, we assume that obtaining a degree from university yields a positive signaling value in the labor market. Alternatively, it is conceivable that leaving university without a degree sends a negative signal in the labor market. Similar to a positive signal when graduating, leaving university might also inform potential employers about unobservable abilities, such as a lack of perseverance or motivation. In the following, we will explain why we think the assumption of a positive signaling value is reasonable. We will then show that even without this assumption, the absolute size of our estimated signaling value remains valid.

Assuming that education sends a positive signal in the labor market is in line with most of the literature. The latter assumption is reasonable as individuals usually have the freedom not to inform employers about an unfinished degree. As leaving university without graduating is not a (negative) signal that has to be necessarily send in the labor market, individuals very often would not mention it in their application. When applying to a job, students who left before graduating would most of the time only include their highest education level obtained and if possible would not make dropout salient. Thus, education can be used as a positive signal in the labor market, although it is unlikely to be used as a negative signal.

Nevertheless, even if a (partly) negative signal exists, the overall value of the estimated signal stays the same. The main difference between graduating yielding a positive signal and graduating meaning to avoid sending a negative signal lies in the relative importance of the human capital effect. The following equations show the implications of this assumption.

In our data, we observe the university-leaving wage $W_i^l(t)$ and the graduation wage $W_i^f(t)$ for individual i at time t both in expectation. Obtaining a positive signal when graduating implies that the university-leaving wage shortly before the degree (at time T) resembles the human capital effect $HC_i^+(T)$, where the "+" indicates that we assume a positive signal here: $signal_i^+$ (likewise a "$-$" indicates the supposition of a negative signal: $signal_i^-$). The following equations show how the signal is calculated assuming it to be positive:

$$
\begin{aligned}
HC_i^{+}(T) &= W_i^{l}(T) \\
HC_i^{+}(T) + signal_i^{+} &= W_i^{f}(T) \\
\Rightarrow \boldsymbol{signal_i^{+}} &= \boldsymbol{W_i^{f}(T) - W_i^{l}(T)}
\end{aligned}
$$

Now we can calculate the signal under the assumption that graduating means avoiding to send a negative signal in the labor market. Hence, the expected graduation wage corresponds to the full human capital value $HC_i^{-}(T)$, whereas the university-leaving wage resembles the human capital value minus the absolute value of the negative signal: $|signal_i^{-}|$.

$$
\begin{aligned}
HC_i^{-}(T) &= W_i^{f}(T) \\
HC_i^{-}(T) - |signal_i^{-}| &= W_i^{l}(T) \\
\Rightarrow |\boldsymbol{signal_i^{-}}| &= \boldsymbol{W_i^{f}(T) - W_i^{l}(T)}
\end{aligned}
$$

We can see that the absolute value of the signaling value is unaffected by the assumption regarding the sign of the signal as $|signal_i^{-}| = signal_i^{+}$. Hence, even without making assumptions on the sign of the signal our estimations are valid. However, as we assume that $W_i^{f}(T) > W_i^{l}(T)$, the human capital value of a degree differs between the two suppositions, with a smaller human capital value under the assumption of a positive signaling value: $HC_i^{+}(T) < HC_i^{-}(T)$.
Note that both outcomes also hold true if we assume that graduating leads to *both* a positive signal due to the degree *and* the avoidance of a negative signal that would be associated with leaving university (see equations below).

$$
\begin{aligned}
HC_i^{both}(T) &= W_i^{l}(T) + |signal_i^{-}| \\
HC_i^{both}(T) + signal_i^{+} &= W_i^{f}(T) \\
&\Rightarrow W_i^{f}(T) = W_i^{l}(T) + |signal_i^{-}| + signal_i^{+}
\end{aligned}
$$

$$
\Rightarrow |\boldsymbol{signal_i^{-}}| + \boldsymbol{signal_i^{+}} = \boldsymbol{W_i^{f}(T) - W_i^{l}(T)}
$$

In this case, measuring the human capital value is not possible without making further assumptions on the size of the two signals, as there exists no state of the world in which no signal is send. Nevertheless, one could calculate a lower and upper bound as the magnitude of the human capital value must lie between the other two scenarios $HC_i^{+}(T) < HC_i^{both}(T) < HC_i^{-}(T)$.
Altogether, the assumptions regarding the sign of the signaling value has an impact on how to interpret the human capital value and how to evaluate the relative importance of human capital vs signaling. However, our estimate of the size of the signal stays valid under all possible assumptions.

E Bachelor vs. master students

In our analysis of the signaling effect, we focus on master students for the reason that they face less ambiguity about both their own abilities and the possible pathways in the counterfactual labor market scenarios. While a master's degree is an additional university degree on top of an existing bachelor degree, bachelor students only achieve their first academic degree when graduating. Therefore, leaving bachelor studies is likely to be associated with higher uncertainty compared with leaving master studies.

First, the potential pathways in the labor market after leaving are more straightforward for master students. Bachelor students who do not obtain a degree will enter the labor market without any academic degree, while leaving master studies always comes with the outside option of "falling back" on one's first academic degree. As most job opportunities for master graduates are also open for bachelor graduates (and so master dropouts), job prospects for leaving are much closer to the graduating plans that master students would pursue. For bachelor students, there exists not only uncertainty with respect to the wage when leaving, but also with respect to the type of job they can do. Non-degree leavers might need to apply to different kind of jobs – potentially even in a different sector – compared to graduates. We mitigate this effect by controlling for licensing, although compared to master students the uncertainty bachelor students face remains higher.

Second, students might face some ambiguity with respect to their own study and work ability. When survey respondents estimate future wages for the two labor market scenarios, they might condition their beliefs on their own abilities, which are ex-ante still unknown to themselves. For the leaving scenario, they might be expecting to find themselves in a bad state, in which their ability turned out to be worse than for the graduating scenario. In the master studies, prior study experience should help to resolve the uncertainty about own study ability and the productivity-enhancing effect of obtaining a degree. However, for bachelor students, graduating informs them about their abilities and part of the premium that we observe for bachelor students might stem from individuals conditioning the counterfactual expectations on the signal about their productivity (Stinebrickner and Stinebrickner, 2012; Arcidiacono et al., 2016). This would lead to an overestimation of the signaling effect. For master students, the premium to finishing the degree is less affected by ambiguity about own ability, as students have already spent several years at university. They thus dispose of information on their skills from their bachelor studies.

When we look at our results, the higher uncertainty for bachelor students makes it unsurprising that we indeed find the magnitude of the estimated signal to be higher for bachelor students (32.8%) than for master students (20.6%). Nonetheless, the patterns for bachelor and master students are still closely comparable for our results in section 4. However, the differences between bachelor and master students become more prominent when we examine heterogeneities in section 5.1. For master students, the signal in general does not depend on background characteristics, which is in line with the signaling theory. For bachelor students, having a migration background, academic parents and a higher perceived job ability positively influence the importance of the signal, although the magnitude of the effects remains moderate compared to the effect size of the signal itself. These heterogeneous effects are likely to be driven by the larger ambiguity that bachelor students face about the two scenarios. For instance, if there is high uncertainty about the segment of the labor market in which a person can work after leaving, and having academic parents is only beneficial if the student enters an academic job, a discrepancy based on parental background may arise.