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The decision to enrol in higher education

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Abstract

In this paper, I analyze how the higher education decision of young adults in Germany depends on their expected future earnings. For this, I estimate a microeconometric model in which individuals maximize life-time utility by choosing whether or not to enter higher education. To forecast individual life cycles in terms of employment, earnings, and family formation under higher education and its alternative, vocational training, I use a dynamic microsimulation model and regression techniques. I take into account that while individuals generally choose between two options, higher education and vocational training, they are aware of multiple potential realizations under both options, such as leaving higher education with a bachelor degree or taking up higher education after first having earned a vocational degree. Using the estimates from the decision model, I simulate the introduction of different tuition fee and graduate tax scenarios. I find that the impact of these education policies on the higher education decision is limited and only few individuals would change their educational decisions as a reaction to these policies.

Keywords: Educational choice, Higher education, Dynamic microsimulation

JEL classification: C53, I23

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1 Introduction

Policy makers around the world believe that human capital is a key factor in determining a country's economic success. However, it is ultimately individuals who decide on how much to invest in their education. Hence, policy makers have an interest in understanding how individuals make their educational decisions and how they can provide incentives to influence these decisions. This paper deals with the question how individual decisions about entering higher education depend on their earnings expectations. Expected earnings can be modified by public policy, either directly through education policy (e.g. the abolition or introduction of tuition fees), or more indirectly, for instance through tax policy.

Analyzing the relationship between educational decisions and (expectations of) life-time earnings goes back to Mincer (1958), Becker (1962), and Ben-Porath (1967). Since then, numerous studies have analyzed how different earnings expectations lead to different decisions concerning (higher) education. One key challenge for these studies is the question how earnings expectations are formed. Some studies, for instance, assume that individuals make educational decisions based on the ex-post realizations of their income profiles, i.e. that individuals are able to perfectly forecast their future earnings. Others have argued that is it more realistic that individuals face some uncertainty with respect to their future earnings profiles. Hence, individuals act upon a limited information set available at the time of the educational decision rather than perfectly forecasting the future (Cunha et al., 2005; Cunha and Heckman, 2007). In the latter case, further assumptions have to be made as to how these earnings are forecasted. Some studies in this spirit have, for instance, assumed that individuals forecast their earnings based on older individuals' trajectories who are otherwise similar to them (see Wilson et al., 2005; Giannelli and Monfardini, 2003; and Flannery and O'Donoghue, 2013). The individuals' earnings expectations are then predicted using regression techniques.

To analyze the role expected earnings play for the higher education choice of young adults in Germany, I follow this literature and estimate a microeconometric model in which individuals maximize their expected life-time utility by deciding whether or not to take up academic training.[1] For the educational decision model, I use a German micro data set that follows a recent cohort of secondary school graduates and observes their educational trajectories after having completed upper secondary school. To forecast an individual's expected life cycle given an educational choice I use a dynamic microsimulation model (Fischer and Hügle, 2020). The dynamic microsimulation model uses survey and administrative data to estimate transition models in employment and family formation and then simulates individual transitions over the life cycle based on the estimated parameters. Estimating in

[1]Note that I use the terms "higher education" and "academic training" interchangeably.

addition a tax function[2] I then translate the forecasted gross into individual net incomes. Importantly, I account for the fact that the current post-secondary education system in Germany contains multiple paths individuals might take. For instance, after entering higher education an individual might either leave the education system with a master degree, a bachelor degree, or no academic degree at all. Similarly, an individual might take into account taking up higher education after having finished a vocational training.

Finally, when estimating the educational decision model, I also take into account non-pecuniary factors such as cognitive skills and parental education that have been shown to be strong predictors of educational decisions (Black and Devereux, 2011). Having estimated the educational decision model, I use the estimates to simulate the introduction of different tuition fee and graduate tax schemes. Estimating the microeconometric model, I find an earnings elasticity of about 0.75, i.e. if expected net lifetime earnings of higher education graduates were to increase by 10%, on average the likelihood of entering higher education would increase by 7.5%. Yet, this elasticity would imply that only few individuals would change their educational choice due to the introduction of tuition fees or graduate taxes.

The remainder of the paper is as follows. Section 2 describes the institutional background of the higher education decision and introduces the microeconometric model. Section 3 presents the data and section 4 explains the regressions and the dynamic microsimulation model. Section 5 then presents the estimation of the educational choice model and simulation results and section 6 concludes.

2 The higher education decision

2.1 Higher education and vocational training in Germany

Currently, 52% of recent German secondary school graduates have a higher education entrance degree (*Hochschulreife*). In general, these individuals face the decision between going to higher education or starting vocational training (*Berufsausbildung*)[3]. Higher education includes university (*Universität*) and university of applied sciences (*Hochschule für angewandte Wissenschaften*)[4] and vocational training comprises dual training (a combination of firm-based training and vocational school) and purely school-based training.[5]

[2] The tax function also accounts for social security contributions. For the sake of simplicity, I use the term "tax function" throughout this paper.

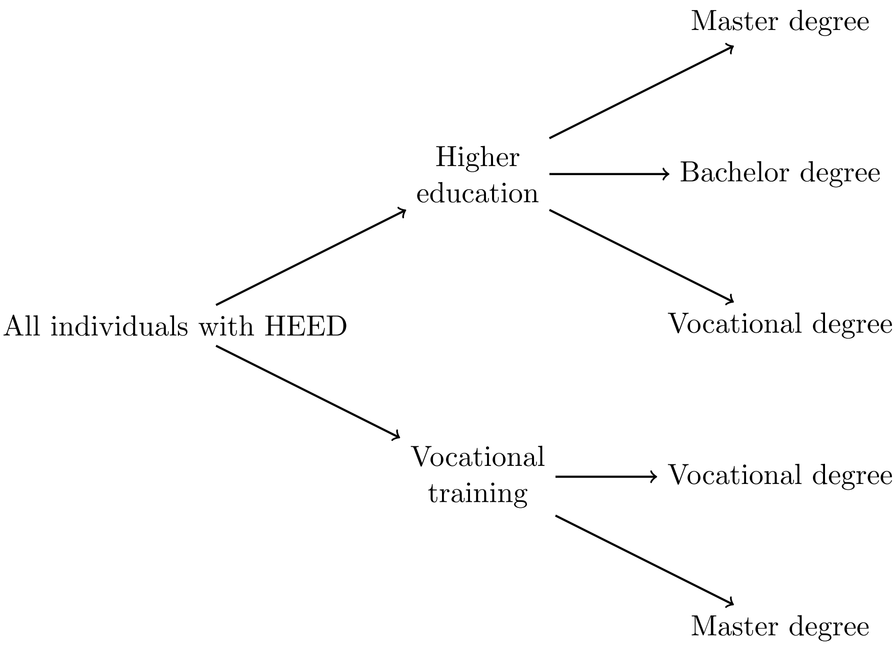
[3] In principle, individuals could also enter the labor market directly without any post-secondary training. However, this does not seem to be an attractive option and almost no individuals choose this path.

[4] Currently, approximately 58% of new higher education entrees attend a university and 42% a university of applied sciences (Autorengruppe Bildungsberichtserstattung, 2018).

[5] Of the individuals who obtained a higher education entrance degree and start a vocational training 66% are in the dual training and 30% in the school-based training system. About 4% enter some form of pre-vocational training

Even though individuals with a higher education entrance degree can be assumed to choose among two options, higher education and vocational training, each option comes along with multiple paths that might potentially be realized from an ex-ante perspective. I model the most frequent of these pathways assuming that these are the potential pathways individual take into account when making their educational choices. Figure 1 sums up these potential paths.

Figure 1: Potentially realizable paths of education



Note: *HEED*=Higher education entrance degree

I assume that there exist three potential paths after having entered higher education: Obtaining a master degree, obtaining a bachelor degree (and not a master degree) and obtaining a vocational degree after having dropped out of higher education. While the master degree is the equivalent to the former *Diploma*, that used to be the most common degree in Germany before the Bologna reforms, it is estimated that a sizeable fraction of 35% (Autorengruppe Bildungsberichtserstattung, 2016) do not enter a master program after graduating with a bachelor degree. Finally, there is a considerable risk of dropping out of higher education as the average dropout rate in bachelor degrees across all subjects is 28% (Autorengruppe Bildungsberichtserstattung, 2018). I assume that individuals who drop out of higher education enter vocational training and obtain a vocational degree.[6]

For individuals who enter vocational training after their higher education entrance degree, I assume that there are only two realizable paths. Either the individual obtains a vocational training degree and

(Autorengruppe Bildungsberichtserstattung, 2018).

[6]Clearly, a part of the 28% who do not finish their bachelor studies enter another study program. Due to a lack of data, however, it is difficult to assess the share of these students. I therefore assume that individuals deciding about whether to enter higher education and assessing the dropout risk of higher education make the simplifying assumption that with a probability of 28% they drop out of higher education and enter vocational training.

leaves the education system entirely or she moves on to higher education and finishes with a master degree. Clearly, also other paths, such as dropping out of academic or vocational training and not obtaining any post-secondary degree, would theoretically be possible. However, they are rather rare so I deem it plausible that individuals do not take them into account when making their educational choice.

2.2 A model of the higher education decision

I assume that individual i associates with each alternative $e = \{he, voc\}$ (i.e. higher education or vocational training) a life-time utility

$$V_{i,e} = \alpha_e LTI_{i,e} + x_i' \beta_e + \varepsilon_{i,e} \tag{1}$$

where $LTI_{i,e}$ is the net lifetime income individual i expects to earn when choosing alternative e and x is a vector of other variables which are potentially important in explaining the higher education decision such as parental education and a measure for cognitive skills. Finally, ε captures all the determinants of life-time utility that cannot be observed by the researcher. It is assumed that ε is uncorrelated with the other terms on the right-hand side.[7]

Following the above discussion that each choice (i.e. higher education or vocational training) is associated with multiple realizable paths, expected lifetime income of entering higher education (he) and vocational training (voc) can be expressed as:

$$\begin{aligned} LTI_i^{he} &= prob^{he\_master} LTI_i^{he\_master} \\ &\quad + prob^{he\_bachelor} LTI_i^{he\_bachelor} \\ &\quad + (1 - prob^{he\_master} - prob^{he\_bachelor}) LTI_i^{he\_voc} \qquad (2) \\ LTI_i^{voc} &= prob^{voc\_voc} LTI_i^{voc\_voc} \\ &\quad + (1 - prob^{voc\_voc}) LTI_i^{voc\_master} \qquad (3) \\ & \qquad (4) \end{aligned}$$

where $prob^{c\_d}$ refers to the probability that the individual will choose c and leave the education system with degree d. For instance, $prob^{he\_bachelor}$ is the probability that the individual enters higher education

[7] Essentially, equation 1 assumes that individuals are risk-neutral. In general, the model could be extended to allow for risk aversion. Fossen and Glocker (2017, 2011) for instance, freely estimate such a parameter. However, estimating such a model with the data used in this paper did not prove successful, as the estimated risk aversion parameters had implausibly large confidence intervals and were very sensitive to the slightest modification of the model. Therefore, I only estimate the model assuming risk-neutrality.

(he) and leaves the system with a bachelor degree ($bachelor$). Hence, the expected lifetime income is just a probablity-weighted sum of lifetime incomes under different realizations.

Finally, the probability that individual i enters higher education can be written as

$$Pr(he_i = 1) = Pr(V_i^{he} > V_i^{voc}) = F(\alpha(LTI_i^{he} - LTI_i^{voc}) + x_i'\beta) \tag{5}$$

where $\alpha = \alpha_{he} - \alpha_{voc}$ and $\beta = \beta_{he} - \beta_{voc}$. $W_i = LTI_i^{he} - LTI_i^{voc}$ is the difference in the expected net lifetime incomes between the two alternatives for individual i. Assuming that the difference in the education-specific error terms, $\varepsilon_{i,he} - \varepsilon_{i,voc}$, is logistically distributed, the likelihood function is given by:

$$L = \prod_{i=1}^{N} F(\alpha W_i + x_i'\beta)^{he_i}(1 - F(\alpha W_i + x_i'\beta))^{(1-he_i)} \tag{6}$$

and the log-likelihood function is

$$LL = \sum_{i=1}^{N}(he_i\ log(F(\alpha W_i + x_i'\beta)) + (1 - he_i)\ log(1 - F(\alpha W_i + x_i'\beta))) \tag{7}$$

In the Logit estimation, equation (7) is maximized with respect to the income weight α and the parameters contained in β.

3 Data

I use two main data sets for the estimation, the National Educational Panel Study (NEPS) (Blossfeld and Von Maurice, 2011) and the Socio-Economic Panel (SOEP) (Goebel et al., 2018). The NEPS follows educational trajectories of different starting cohorts (SC), from newborns (SC1) to adults (SC6). I use the SC4, which, starting in 2010, has been following the educational careers of about 13,000 pupils starting in 9th grade. The educational decisions after secondary school of the SC4 cohort are the ones I am analyzing. Table A1 in the appendix shows the descriptive statistics for the final sample with which the decision model will be estimated.

The SOEP is a household panel that started in 1984 and currently surveys about 30,000 individuals. I use the SOEP for two purposes. First, the SOEP is the main data base for the dynamic microsimulation model outlined in Fischer and Hügle (2020) (see Section 4.3 for more details). Second, I use the SOEP waves from 2000 to 2012 to estimate wage parameters, and a tax function by which life-time income profiles are constructed. Restricting the data set to waves until 2012 is due to the timing of the education decisions analyzed in this study: The NEPS cohort of interest was in 11th grade in 2012. I assume that this is around the time when these individuals made their educational decisions and hence the point in time from which they draw their information set. Finally, in order to make assumptions about training length, income during training, and dropout probability I draw on additional sources, particularly on the Autorengruppe Bildungsberichtserstattung (2014, 2016, 2018).

4 Parameter estimation and life-cycle simulation

In this section, I describe the estimation of wage regressions, the tax function, and how the life cycles are constructed using dynamic microsimulation. Together with the forecasted life cycles, the parameters of the wage regressions are used to predict hourly wages and annual labor earnings over the life cycle. The tax function is then used to translate gross into net earnings.

4.1 Gross hourly wages

To predict earnings over the life cycle, I estimate Mincer-type wage regressions separately for education (i.e. for individuals with higher education and individuals with vocational degree and higher education entrance degree)[8] and gender. The estimating equations are defined as

$$log(wage_{it}^{he}) = x_{it}'\beta^{he} + \varepsilon_{it}^{he} \quad (8)$$

$$log(wage_{it}^{voc}) = x_{it}'\beta^{voc} + \varepsilon_{it}^{voc} \quad (9)$$

where equation 8 is estimated using the sample of higher education graduates and equation 9 using individuals with vocational degree and higher education entrance degree.[9] Importantly, I only use observations with a master or an equivalent degree for estimating equation 8.[10] $log(wage)_{it}$ is the log gross hourly wage of individual i in year t. x is a vector of covariates including a fourth-order polynomial of labor market experience, an indicator for migration background, nine industry dummies and dummies for civil service and self-employment, and a vector of year dummies. In addition, x also includes a vector of dummies for the German states. They are fundamental for generating the variation in expected lifetime income gaps between academic and vocational training across states and hence across individuals. The idea is that when making the educational choice each individual faces different expected lifetime income gaps between academic and vocational training because of the state she lives in.[11] Finally, equation 8 also controls for having a university of applied science degree.

[8] Note that, in this study, the term *vocational degree* implies a higher education entrance degree, even though it is not always explicitly stated.

[9] Using the parameter estimates of the log wage equation, the hourly wage of individual i can be computed using the formula $\hat{w}_i = exp(x_i'\hat{\beta} + 0.5\hat{\sigma}^2)$, where x is the vector of covariates, $\hat{\beta}$ is the vector of coefficient estimates of the log wage equation, and $\hat{\sigma}^2$ is an (unbiased) estimator of the model error in the log wage regression (Cameron and Trivedi, 2009).

[10] For the estimation of the bachelor wage penalty, see Section 4.1.1.

[11] Section 6 will discuss this issue further.

Equations 8 and 9 are estimated by OLS. Hence, the consistent estimation of the wage parameters relies on a *selection-on-observables* assumption, i.e. the assumption that conditional on the other explanatory variables the education level is not correlated with unobservables such as ability and motivation.

There are two selection issues that need to be addressed. The first is non-random selection into education, i.e. into higher education and vocational training, as individuals are choosing their education levels. Another potential selection bias might arise due to non-random selection into the labor force, i.e. the fact that the estimation samples only contain working individuals for whom an hourly wage can be computed. A natural solution for these two problems is the estimation of selection-corrected wage equations. This means that one first estimates selection equations for the education and work choices using Probit models and then adds selection correction terms to the set of x variables in the wage equations.

For the estimation of selection-corrected wage equations exclusion restrictions are required, i.e. variables that affect the education and work choices but do not directly enter the wage equations.[12] Here, I follow the literature and use marital status and dummies for the presence of children in the household between the ages 0 and 5 and between 6 and 17 as exclusion restrictions for the selection into work (for a similar approach see Steiner and Lauer (2000) and Fossen and Glocker (2017, 2011)). For the selection into education, I follow Fossen and Glocker (2017, 2011) and use parental variables before the individual graduates from secondary school such as indicator variables for parental education, for whether they work, and for whether they were born in Germany. However, one should bear in mind, particularly with respect to the selection-into-education corrections, that the advantage of using the selection corrections crucially depends on the validity of the exclusion restrictions. It is plausible to assume that variables that capture parental attitudes, behavior, and characteristics (such as parental education and whether parents work) might be correlated with the unobservables in the wage equation, such as an individual's ability and motivation. For these reasons, I use the wage specification without selection corrections as my main specification, but also report the results using two additional wage specifications: one where I only use a selection correction for work and one where I use a selection correction for both education and work. The latter is, due to the argument above, the least preferred specification. The main results of the paper, however, such as the elasticity of the educational choice with respect to lifetime income, barely depend on which specification is used, as will become clear below.

Tables A2-A5 in the appendix display the regression results for the selection and wage regressions.

[12]Technically, the model could also be identified without exclusion restrictions due to the non-linearity of the selection correction terms in the observable variables.

For the main specification without selection corrections, there are wage penalties for having a migration background between 12% (men and women with higher education) and 21% (men with vocational degrees) and a penalty for having a university of applied sciences degree (compared to university) between 14% (men) and 19% (women).

4.1.1 Bachelor wage penalty

As individuals potentially finish their academic career with a bachelor degree, we need to make assumptions concerning the wage profile of such graduates. In order to estimate a potential hourly-wage penalty of bachelor relative to master degrees, I use SOEP waves from 2010 to 2012[13] and estimate a similar wage equation to (8). I find a bachelor wage penalty of 10.1% for men and 13.5% for women. This is comparable to the estimate of Christoph et al. (2017) who use administrative data and find a wage penalty of about 10% at age 30.

4.2 The tax function

As, by assumption, lifetime utility is a function of individual *net* income, it is necessary to translate expected gross into net incomes. To do this, I approximate the tax-and-contributions system[14] of the year 2012 (by assumption the year of the educational choice) by estimating the function

$$\begin{aligned} taxrate_{it} = \quad & \beta_0 + \beta_1 grossinc_{it} + \beta_2 grossinc_{it}^2 + \beta_3 grossinc_{it}^3 + \beta_4 grossinc_{it}^4 \\ & \beta_5 grossinc_{it}^5 + \beta_6 nr\_children_{it} + \beta_7 married_{it} + \varepsilon_{it} \end{aligned} \tag{10}$$

with data for the years 2010-2012 where $taxrate_{it}$ is the tax rate of individual i in period t[15], *grossinc* is the individual annual gross labor income, *married* a dummy for being married, and *nr_children* is the number of children.

Table A6 in the appendix displays the estimated coefficients and Figure A1 in the appendix plots the predicted average tax rates for different annual labor incomes for an unmarried individual without children. Somewhat surprisingly, the curve of the average tax rate is downward sloping starting at an individual annual labor income of about 75,000 Euros. However, this part of the slope concerns no individual as the maximum predicted annual earnings of any individual is about 70,000 Euros.

[13]The SOEP's ISCED11 classification that distinguishes between master and bachelor degrees is only available from 2010 on.

[14]For simplicity, I ignore transfers in this analysis. Yet, as Fischer and Hügle (2020) show, their quantitative importance for individuals with higher education entrance degree is very limited compared to taxes and social security contributions.

[15]$taxrate = \frac{\text{individual annual gross labor income} - \text{individual annual net labor income}}{\text{individual annual gross labor income}}$

4.3 Life-cycle simulation

Having estimated the corresponding hourly wage and tax parameters, the next step is to forecast the individual life cycles. Here, we need to make assumptions about the individuals' perceptions of their potential training trajectories, such as the probabilities of different realized paths, training length, and the earnings while in training. I make these assumptions based on different aggregate statistics as of 2012 (or before), as this was the time period when individuals had to decide about the enrolment into higher education.

In general, I assume that all individuals make their decision whether or not to enter higher education at the age of 20[16] and then make a transition into one of the two alternatives. In academic training, an individual drops out with 28% (Autorengruppe Bildungsberichtserstattung, 2014). Given she finishes the bachelor degree, she will leave higher education with a probability of 36%, and move on to graduate with a master degree with 64% (Autorengruppe Bildungsberichtserstattung, 2018). In 2012, the average duration until graduation with a master degree or diploma was 11.2 semesters (Autorengruppe Bildungsberichtserstattung, 2018). I therefore assume that if the individual continues after the bachelor, she will leave the education system with a master degree after six years. I further assume that an individual has net earnings of 474 Euros while in academic training which is the average of the sum of labor earnings and student grants in Germany (Middendorff et al. (2017) and own calculations).

If, in contrast, an individual enters vocational training, she is assumed to finish after three years of training, the official duration of most such training programs. With a probability of 35%, she will afterwards take up academic training and I assume that she finishes with a master degree in six years. Furthermore, I assume that while in vocational training an individual has net earnings of 632 Euros which is the weighted average of those who earn salaries (*Ausbildungsvergütung*) in dual training and those who receive pupil grants in school-based training.

After graduation, individuals are assumed to enter the labor market and retire at the age of 67, the official retirement age for this cohort in Germany. In order to simulate the individual life cycles in terms of employment and family formation (i.e. marriage, fertity, and divorce) I use a modified version of the dynamic microsimulation model outlined in Fischer and Hügle (2020). The modified dynamic microsimulation model has two stages: In the first stage, transition models for the processes of employment and family formation are estimated via different discrete-choice models. The key explanatory variables of these models are indicators that capture the academic and vocational degrees and indicators for being in academic or vocational training. In addition, the models control

[16]The median age of entry into higher education was 19,7 in 2012 (Autorengruppe Bildungsberichtserstattung, 2018).

for migration background, dummies for the federal states, year dummies, and lagged variables of employment states and family formation. All transition models are estimated using SOEP data. In order to guarantee that the simulated individual transitions will follow predicted aggregate trends, so-called *fractional regression models* (Papke and Wooldridge, 1996, 2008) are estimated. These fractional regression models use the shares of different employment states, and birth, marriage, and divorce rates as dependent variables and regress them on polynomials of age and cohort dummies. While the fractional regression models for employment are estimated using SOEP data, administrative data is used for the models of family formation.

In the second stage, individual transitions are sequentially simulated, starting at age 18. For this, using the parameter estimates of the transitions models one first predicts individual fertility, marriage, and employment probabilities. Then these predictions are multiplied with random draws from the unit interval. Finally, individuals are selected for transitions based on these modified probabilities until the aggregate targets (which are predicted using the fractional regression estimates) are met. In the end, each individual in the decision sample is assigned the average age-specific values conditional on gender, migration background, and federal state.

Having forecasted the individual life cycles in terms of employment and family formation, I can then simulate the annual gross earnings over the life cycle by using the estimates of the hourly regressions. Importantly, each individual has then one estimate for the expected lifetime income under each realizable path. Annual net income can then be computed using the yearly gross income and the predicted tax rates for this income and given the (simulated) presence of children and marital status. Tables A7 and A8 in the appendix show the average predicted net and gross life-time earnings for higher education and vocational training separately for men and women and the different wage specifications.[17]

As expected, life-time earnings are substantially higher for men than for women across all paths and finishing with a master degree (HE) is associated with higher life-time earnings than vocational training (VOC). Comparing the different wage specifications, with and without selection corrections, the tables show that the selection corrections lead to reduced simulated lifetime earnings, particularly for the specification with selection corrections for both education and work. However, one should bear in mind that the latter specification is the one that should be seen with caution with respect to its validity. Finally, the implied average tax rate is much larger than the one for similar gross incomes simulated in Fischer and Hügle (2020). For instance, while the implied average tax rate for gross incomes of 1.427 Mio. Euros (the simulated lifetime income of men under higher education in the base

[17]For the sake of clarity, I only present the two "standard" paths here, i.e. choosing higher education and finishing with a master degree and choosing vocational training and finishing with a vocational degree.

specification) is about 38.5%, Fischer and Hügle (2020) report an estimate of about 31% for a similar income level. The difference, however, can mainly be explained by the fact that Fischer and Hügle (2020) exclude pension insurance contributions from their analysis.

5 Results

5.1 Decision model: Parameter estimation

Table 1 shows the estimates of the Logit model outlined in equation 7 for the three wage specifications discussed above. The main variable of interest is the difference in expected net lifetime income between entering higher education and vocational training, $\Delta LTI = LTI^{he} - LTI^{voc}$. In addition, I control for other determinants of the higher education decision: Gender, parental education, parental occupation, migration background, and cognitive skills. For parental education, I define three categories with respect to the parent with the highest education level: No higher education entrance degree, a higher education entrance degree (but no higher education degree), and a higher education degree. Hence, if one parent has a higher education degree and the other has no higher education entrance degree, the parents are classified as having a higher education degree. Similarly, parental occupation, which serves as a proxy for parental income, has three categories which are defined with respect to the parent with the highest EGP class: High (e.g. managers, high-ranked civil servants, highly qualified white collar workers), medium (e.g. qualified white collar workers, master craftsmen) and low. Hence, if one parent has a high EGP class and the other has a medium class, the parents are classified as having a high EGP class.[18] Cognitive skills are measured by the tested competencies in different fields such as perceptual speed, reasoning, and numeracy skills.

The statistically significant positive coefficient estimate of ΔLTI indicates that an increase in the expected net lifetime-income gap between higher education and vocational training increases the probability of entering higher education. In order to interpret its magnitude, one can use the parameter estimates and predict how the enrolment probabilities would react if net lifetime incomes for those with a higher education degree would increase by 10%. I find that such a 10% increase would rise the higher education enrolment probability, on average, by about 7.5%, which implies an "elasticity" of 0.75.[19][20][21]

For the control variables, one can use the estimated coefficients and compute the average marginal

[18]See Biewen and Tapalaga (2017) for a similar categorization.

[19]The elasticities for the different underlying wage specifications are: 0,757 (no selection correction), 0.762 (correction for selection into work), 0.749 (correction for selection into work and education).

[20]This quantity can be computed by first computing the relative change in the individual choice probabilities after increasing the net lifetime income of academics by 10% and then averaging the relative change over all individuals.

[21]This elasticity is very close to the elasticities found in Fossen and Glocker (2017), which are around 0.8.

Table 1: Enrolment decision: Logit estimates

	Baseline: No selection correction	Selection into work	Selection into work and education
$\Delta LTI/10{,}000$	0.0863***	0.0925***	0.0956***
	(0.0340)	(0.0355)	(0.0366)
Female	0.1710***	0.1625***	0.0300
	(0.0737)	(0.0731)	(0.0832)
Parents: HE entrance deg.	0.4783***	0.4794***	0.3876***
	(0.0899)	(0.0899)	(0.0950)
Parents: HE deg.	0.9701***	0.9703***	0.8834***
	(0.0932)	(0.0932)	(0.0975)
Parents: Medium occ.	0.0379	0.0379	0.0441
	(0.1164)	(0.1165)	(0.1165)
Parents: Max. occ.	0.2878***	0.2877***	0.2960***
	(0.1251)	(0.1251)	(0.1251)
Migration background	0.5360***	0.5318***	0.5049***
	(0.1503)	(0.1505)	(0.1536)
Cognitive skills	0.7878***	0.7877***	0.7891***
	(0.0483)	(0.0483)	(0.0483)
Constant	−0.6545***	−0.6364***	−0.4935***
	(0.1573)	(0.1511)	(0.1224)
N	4,106	4,106	4,106

Notes: This table displays the Logit coefficients and standard errors (in parentheses) of estimating the log-likelihood function (equation 7). The different columns represent different underlying wage specifications used to simulate lifetime incomes. The estimates in the left column represent the estimation where lifetime incomes are based on the wage specifications without selection correction. The middle and the right column represent the estimation where lifetime incomes are based on wage specification with selection correction for selection into work and selection into both work and education, respectively. $\Delta LTI = LTI^{he} - LTI^{voc}$ is the difference in the expected individual net lifetime income between higher education and vocational training. Significance levels: $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$.
Source: NEPS, SOEP, own calculations.

effects (not shown in the tables). For the base specification this computation shows that parental education has a strong positive impact: Having at least one parent with a higher education entrance degree increases the probability of entering higher education by about 9 percentage points, while having at least one parent with an academic degree increases this probability by about 18 percentage points (both effects compared to the base category of not having at least one parent with a higher education entrance degree). Parental occupation, in contrast, only has a small effect on higher education enrolment: Having at least one parent with high occupational status increases the likelihood to enter academic training by about 5.5 percentage points.[22] An increase in cognitive skills by one standard deviation increases the likelihood of entering academic training by about 15 percentage points. In addition, there is a strong positive effect of having a migration background on the probability of higher education enrolment of more than 9.5 percentage points.

[22]The effects of parental education and occupation are similar in magnitude to Biewen and Tapalaga (2017).

5.2 Simulation of tution fees and graduate taxes

In order to assess how strongly a change in educational policies would impact the higher education decision, I simulate different tuition fee and graduate tax scenarios. As to tuition fees, I simulate three different scenarios: annual fees of (i) 2,000 Euros, (ii) 4,000 Euros, and (iii) 6,000 Euros. While the latter is close to the actual average cost of tuition per student and year, the first two scenarios would be more likely to receive public support.[23] I assume a system with deferred repayment and income-contingent loans, i.e. individuals gradually pay back their debt if their individual net income exceeds a certain threshold. Such a system has been in place in some Western countries such as England, Australia, and New Zealand and has been described in the theoretical literature as being superior in terms of efficiency and equity compared to a system where fees are to be paid up-front (see, for instance, Barr, 2004, and Chapman, 2006). A main reason is that up-front tuition fees might cause liquidity constraints and particularly deter individuals from low socio-economic background from enrolling. In addition, Lergetporer and Woessmann (2019) find that designing tuition fees as deferred income-contingent payments would substantially increase public support for fees.

I set the net income threshold above which an individual has to pay back tuition debt to 20,000 Euros and the repayment rate, i.e. the share of net income above the threshold that has to be paid back, to 0.2. Furthermore, I assume that there are interest rates. The key feature and the main difference to the nature of graduate taxes is that the maximum amount an individual would have to pay back over her lifetime is limited, for instance to 36,000 Euros if tuition fees are 6,000 Euros annually and an individual studies for 6 years.

In contrast to tuition fees, graduate taxes imply that each higher education graduate pays a share on her individual net income, independently of the total amount already paid, i.e. the total amount of graduate taxes depend on income earned over the lifetime.[24] This implies that a graduate tax might imply a much higher total debt over the lifetime. Graduate taxes have been discussed as an alternative to tuition fees, especially in Great Britain.[25] Here, I simulate three different scenarios: A graduate tax of (i) 1%, (ii) 2%, and (iii) 3% of individual net income.

Tables 2 and 3 show the simulation results. It becomes clear that none of the tuition fee or graduate tax scenarios would dramatically change the average enrolment probabilities. As for tuition fees, the largest reform, the introduction of annual tuition fees of 6,000 Euros, would only reduce the average enrolment probability from 67.34% to 65.86%. For graduate taxes, the results are similar in

[23] Some West German states temporarily collected tuition fees starting in 2006/2007. These fees were usually about 500 Euros per semester, and hence 1,000 Euros per year.

[24] Some proposals of graduate taxes also imply that the total amount paid is limited to some level. In this simulation exercise, I assume that there is no such limit.

[25] Supporters of graduate taxes include, for instance, the former UK prime minister Gordon Brown.

magnitude. Comparing the two different policies one finds that the effects tuition fees of about 6,000 Euros per year have on enrolment correspond to the effects a graduate tax of 2% has on enrolment. The reason is that these two schemes are of a similar absolute size and imply a total tuition debt of about 35,000 Euros. A larger graduate tax of 3% would cause larger responses and a reduction in the enrolment probabilities of more than 3%.

Table 2: Effect of different tuition fee schemes

Scenario	Probability (in %)	abs. change (in percentage points)	rel. change (in percent)
Base	67.34		
2,000 Euros/year	66.73	-0.61	-0.91
4,000 Euros/year	66.24	-1.10	-1.63
6,000 Euros/year	65.86	-1.48	-2.20

Notes: This table displays the effects of different tuition fee schemes on the average enrolment probabilities. *Base* = Base scenario. The lines below describe the different tuition fee scenarios. For instance, *2,000 Euros/year* describes the effects of an introduction of annual tuition fees of 2,000 Euros. *Probability* = Probability of enroling in higher education. *abs. change* = absolute change in enrolment probability. *rel. change* = relative change in enrolment probability.
Source: NEPS, SOEP, own calculations.

Table 3: Effects of different graduate tax schemes

Scenario	Probability (in %)	abs. change (in percentage points)	rel. change (in percent)
Base	67.34		
1% graduate tax	66.65	-0.69	-1.03
2% graduate tax	65.94	-1.40	-2.07
3% graduate tax	65.24	-2.10	-3.13

Notes: This table displays the effects of different graduate tax schemes on the average enrolment probabilities. *Base* = Base scenario. The lines below describe the different graduate tax scenarios. For instance, *1% graduate tax* describes the effects of an introduction of a graduate tax of 1%. *Probability* = Probability of enroling in higher education. *abs. change* = absolute change in enrolment probability. *rel. change* = relative change in enrolment probability.
Source: NEPS, SOEP, own calculations.

That the effects of the simulated policies on higher education enrolment are limited in magnitude seems plausible given that the total amount of debt an individual would accumulate in systems with tuition fees or graduate taxes is quite small relative to the expected lifetime income. However, these results partially contrast recent research of the effects of tuition fees in Germany (see, for instance, Bietenbeck et al., 2020; Bruckmeier and Wigger, 2014; and Hübner, 2012). Exploiting the variation in the introduction of fees across the German states starting in the mid-2000s, these studies estimate the effect on enrolment via difference-in-differences estimations. While Bietenbeck et al. (2020) and Hübner (2012) find that the introduction of tuition fees reduced enrolment by about 3.9 and 2.7 percentage points, respectively, Bruckmeier and Wigger (2014) finds a smaller negative effect of 0.9 percentage points which is not statistically significant. At a first glance it might be surprising that these studies find a much larger negative response of tuition fees on the enrolment decision, given that the tuition fees analyzed in those studies where mostly 1,000 Euros per year. However, there is a key difference between the hypothetical tuition fee reforms analyzed here and the actual ones implemented in the mid-2000s: While the mid-2000s reforms made students pay their fees up-front, the fee scheme simulated here would include a deferred payment, and only if income exceeds a certain threshold. As precisely the up-front nature of the tuition fees of the mid-2000s might have prevented individuals from lower socio-economic backgrounds from higher education, it is plausible to assume that the tuition fee should imply larger negative effects on enrolment than the schemes considered here.

As argued above, the hypothetical fee system with deferred payment analyzed here is closer to the English tuition fee system. In 1998, England introduced tuition fees and increased them in 2006 and further in 2012. At the same time, however, England also increased financial support leading to a similar system to the one analyzed here. Indeed, Murphy et al. (2019) and Azmat and Simion (2020) find only small effects of the introduction (in 1998) and increase of tuition fees (in 2006 and 2012) on enrolment. In fact, these studies find that the introduction of sizeable tuition fees decreased the enrolment probability of individuals of higher socio-economic background much more than those of lower socio-economic background. The reason, the authors state, is that while individuals of lower socio-economic background received generous financial support those of high socio-economic background often did not and had to bear the tuition fees by themselves. These studies suggest that the effects of enrolment one can expect from the introduction of tuition fees crucially depend on whether tuition fee (re)payment is up-front or deferred and whether repayment is income-contingent.

6 Conclusion

This paper analyzes the role of expected earnings for the decision to enrol in higher education. To do so, I forecast life cycles using dynamic microsimulation and regression techniques. Then, I estimate a microeconometric model where individuals maximize expected life-time utility by choosing whether to participate in academic training. I assume that, while making their decision, individuals take into account that there is uncertainty with respect to the educational path they will follow in the future. I find an elasticity of about 0.75, i.e. a 10% increase in expected individual net lifetime income for higher education degrees would increase the average likelihood of entering higher education by about 7.5%. Finally, I simulate different tuition fee and graduate tax scenarios. I find that tuition fees of a "plausible" size would cause only small changes in enrolment behavior.

One argument in favor of tuition fees has been that tuition fees could help academic institutions increase the quality of their education. The analysis in this paper suggests that governments could raise some additional revenue for higher education by introducing or increasing tuition fees or graduate taxes without deterring many students from entering higher education. However, the recent literature on the German experience with tuition fees in the mid-2000, also suggests that the effect of tuition fees crucially depends on whether they are to be paid up-front or whether there is deferred payment together with income-contingent loans instead. While up-front fees may indeed have a strong negative effect on enrolment, deferred fees might be much more favorable preventing liquidity constraints of students from lower socio-economic backgrounds.

Key to the internal validity of the approach used in this paper are assumptions on how individuals form expectations, particularly about future earnings, but also concerning academic dropout risks etc. However, validating these assumptions is a difficult task, especially as data sets which contain individuals' subjective expectations about future outcomes are only scarcely available. Yet, there is a growing body of research that tries to capture such expectations (see e.g. Wiswall and Zafar (2015) and Arcidiacono et al. (2020) for recent examples). Comparing "objective" and subjective expectations is a promising area for future research. It would be particularly interesting to conduct an analysis of the heterogeneity of such expectations. Here, I assumed for instance, that individuals have the same probability of obtaining a master degree, given that they already have obtained a bachelor degree. It might be, however, that there are structural differences between individuals.

A similar aspect concerns the assumption in how far an individual's wage expectations are determined by the state or region she lives in. Here, as in the studies with a similar approach in the literature, I assume that individuals basically form their wage expectations for higher education and vocational training based on the wages they observe in their state. This assumption might be too strong for individuals who expect to move to other regions in Germany and therefore have different expectations than individuals from the same state who plan to stay in their state. Future research could aim at investigating these heterogeneities.

Another avenue for future research is the consideration of earnings risk in the educational decisions. A few studies in the literature have modeled earnings and earnings risk jointly (see Fossen and Glocker, 2017; Fossen and Glocker, 2011; and Buchinsky and Leslie, 2010). The idea is that individuals might take into account that their choices are "risky" in different dimensions: For instance, individuals might not associate an educational choice with a single estimate of lifetime income but rather a whole distribution of expected earnings and be uncertain as to which "draw" of this distribution will be realized. Future research might use the simulated life cycles and combine them with a more elaborate decision making model that allows for different degrees of risk aversion.

Finally, it should be noted that individuals who enrol in higher education also decide on a subject they want to specialize and major in (see Altonji et al. (2016) for an overview over this literature). In the case of Germany, Hügle (2021) analyzes this choice by modeling *fields of study*. It would be a promising avenue of research to analyze how these two neighboring fields of the literature could be combined, i.e. to model how individuals decide jointly about studying in general and choosing specific fields of study or training programs in particular.

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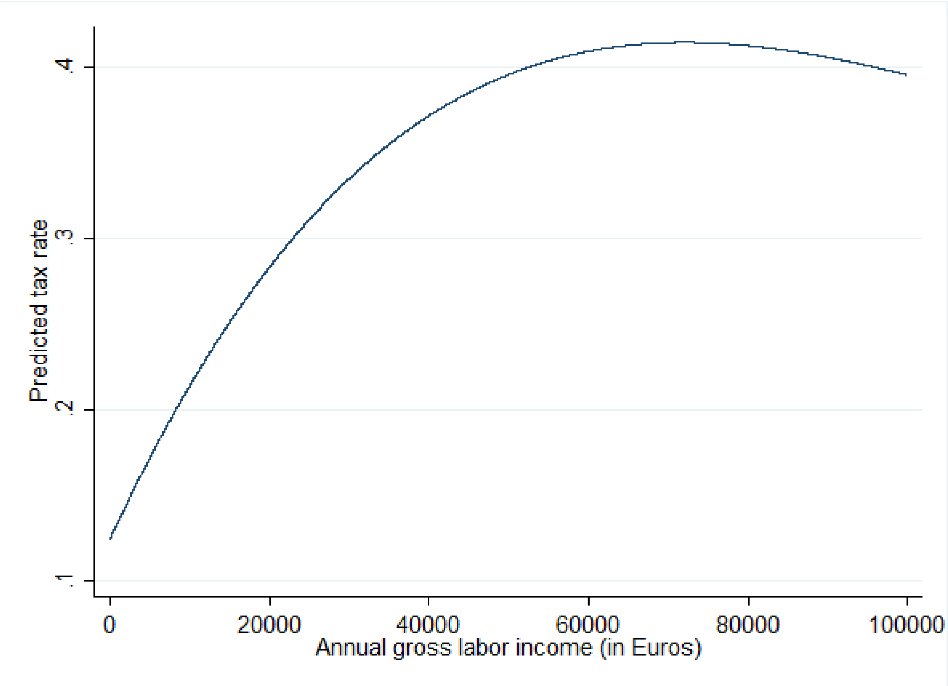
Appendix

Figure A1: Tax function



Notes: This graph shows the predicted tax function for an unmarried individual without children. “Taxes” also include social security contributions.
Source: SOEP, own calculations.

Table A1: Descriptive statistics, NEPS sample

	Mean	Std. dev.
Female	0.54	0.50
Migration background	0.07	0.26
Transition into higher education	0.67	0.47
Cognitive skills	0.64	0.83
Parental education: No HEED	0.39	0.49
Parental education: HEED	0.24	0.43
Parental education: Academic degree	0.36	0.48
Parental occupation: Low	0.11	0.31
Parental occupation: Middle	0.44	0.50
Parental occupation: High	0.45	0.50
Parents germanborn: n.a.	0.29	0.46
Parents germanborn: no	0.06	0.23
Parents germanborn: yes	0.65	0.48
Father working at age 15: n.a.	0.16	0.37
Father working at age 15: no	0.05	0.22
Father working at age 15: yes	0.79	0.41
Mother working at age 15: n.a.	0.14	0.35
Mother working at age 15: no	0.11	0.31
Mother working at age 15: yes	0.75	0.43
N	4,106	

Notes: This table displays mean and standard deviation of the variables used in the analysis for the NEPS sample. Abbreviations: *HEED*= Higher education entrance degree.
Source: NEPS, own calculations.

Table A2: Selection into education and work, Probit estimates

	Men, education	Women, education	Men, work	Women, work
main				
Parental education: HEED	0.859***	0.926***		
	(0.0121)	(0.0115)		
Parental education: n.a.	-0.398***	-0.205***		
	(0.0161)	(0.0152)		
Father working	0.0626***	0.197***		
	(0.0197)	(0.0204)		
Father working: n.a.	0.250***	0.167***		
	(0.0232)	(0.0231)		
Mother working	-0.157***	0.0796***		
	(0.0113)	(0.0116)		
Mother working: n.a.	-0.186***	0.0857***		
	(0.0125)	(0.0123)		
Parents germanborn	0.211***	0.0391*		
	(0.0222)	(0.0219)		
Parents germanborn: n.a.	0.577***	0.260***		
	(0.0218)	(0.0215)		
Experience^2/100			0.460***	0.0139
			(0.0222)	(0.0164)
Experience^3/1,000			-0.165***	-0.00833
			(0.0150)	(0.00911)
Experience^4/100,000			0.167***	-0.00720
			(0.0252)	(0.0131)
Migration background			-0.202***	-0.392***
			(0.0122)	(0.0133)
Married			-0.809***	0.511***
			(0.0125)	(0.0122)
Children aged 0-5 in hh.			-0.848***	-0.0939***
			(0.0113)	(0.0130)
Children aged 6-17 in hh.			0.188***	-0.200***
			(0.0105)	(0.0108)
Constant	-1.179***	-1.370***	1.610***	-1.169***
	(0.0269)	(0.0275)	(0.0367)	(0.0293)
State dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	99247	110592	109368	96666

Notes: This table displays the results of Probit regressions. Each column represents a separate regression. Columns 1 and 2 represent the selection-into-education equation. The dependent variable is a binary indicator whether the individual has an academic degree. Columns 3 and 4 represent the selection-into-work equation. The dependent variable is a binary indicator whether the individual is working.
Source: SOEP, own calculations.

Table A3: Wage regressions, no selection correction

	Men, HE	Men, VOC	Women, HE	Women, VOC
Experience/10	1.189***	0.690***	0.718***	0.546***
	(0.0461)	(0.0664)	(0.0482)	(0.0553)
Experience^2/100	-0.676***	-0.282***	-0.416***	-0.264***
	(0.0449)	(0.0665)	(0.0569)	(0.0678)
Experience^3/1,000	0.172***	0.0504**	0.109***	0.0640**
	(0.0163)	(0.0245)	(0.0237)	(0.0291)
Experience^4/100,000	-0.163***	-0.0307	-0.108***	-0.0647
	(0.0195)	(0.0298)	(0.0316)	(0.0397)
Migration background	-0.123***	-0.214***	-0.117***	-0.135***
	(0.0109)	(0.0124)	(0.0134)	(0.0117)
UAS	-0.137***		-0.185***	
	(0.00662)		(0.00851)	
Constant	2.401***	2.078***	2.455***	2.193***
	(0.0318)	(0.0482)	(0.0308)	(0.0325)
State dummies	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	15408	6391	11381	7332

Notes: This table displays the results of linear regressions without selection corrections using the log hourly gross wage as the dependent variable. Each column represents a separate regression. *HE* (*VOC*) implies that the estimation sample is based on individuals with a higher education (vocational training) degree. *UAS*=University of applied sciences degree.
Source: SOEP, own calculations.

Table A4: Wage regressions, selection-into-work correction

	Men, HE	Men, VOC	Women, HE	Women, VOC
Experience/10	1.144***	0.648***	0.700***	0.530***
	(0.0464)	(0.0671)	(0.0482)	(0.0559)
Experience^2/100	-0.649***	-0.255***	-0.368***	-0.237***
	(0.0450)	(0.0668)	(0.0571)	(0.0690)
Experience^3/1,000	0.164***	0.0420*	0.0913***	0.0521*
	(0.0163)	(0.0246)	(0.0238)	(0.0297)
Experience^4/100,000	-0.152***	-0.0195	-0.0885***	-0.0483
	(0.0196)	(0.0299)	(0.0316)	(0.0406)
Migration background	-0.0708***	-0.174***	-0.133***	-0.138***
	(0.0126)	(0.0153)	(0.0135)	(0.0121)
Correction term work	-0.180***	-0.151***	0.179***	0.0390*
	(0.0219)	(0.0341)	(0.0196)	(0.0214)
UAS	-0.134***		-0.184***	
	(0.00664)		(0.00849)	
Constant	2.667***	2.309***	2.409***	2.188***
	(0.0453)	(0.0711)	(0.0311)	(0.0328)
State dummies	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	15356	6378	11348	7297

Notes: This table displays the results of linear regressions with a selection-into-work correction using the log hourly gross wage as the dependent variable. Each column represents a separate regression. *HE* (*VOC*) implies that the estimation sample is based on individuals with a higher education (vocational training) degree. *UAS*=University of applied sciences degree.
Source: SOEP, own calculations.

Table A5: Wage regressions, selection-into-work and selection-into-education correction

	Men, HE	Men, VOC	Women, HE	Women, VOC
Experience/10	1.146***	0.644***	0.708***	0.535***
	(0.0463)	(0.0670)	(0.0481)	(0.0559)
Experience^2/100	-0.650***	-0.250***	-0.370***	-0.241***
	(0.0449)	(0.0667)	(0.0570)	(0.0690)
Experience^3/1,000	0.164***	0.0400	0.0903***	0.0532*
	(0.0163)	(0.0246)	(0.0237)	(0.0297)
Experience^4/100,000	-0.152***	-0.0171	-0.0859***	-0.0493
	(0.0195)	(0.0299)	(0.0316)	(0.0406)
Migration background	-0.0644***	-0.169***	-0.128***	-0.135***
	(0.0126)	(0.0154)	(0.0135)	(0.0121)
Correction term work	-0.180***	-0.154***	0.179***	0.0392*
	(0.0218)	(0.0341)	(0.0195)	(0.0214)
Correction term education	-0.299***	-0.225***	-0.0780***	-0.0302*
	(0.0376)	(0.0676)	(0.0120)	(0.0159)
UAS	-0.126***		-0.177***	
	(0.00670)		(0.00854)	
Constant	2.842***	2.466***	2.501***	2.228***
	(0.0503)	(0.0852)	(0.0341)	(0.0391)
State dummies	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	15356	6378	11348	7297

Notes: This table displays the results of linear regressions with a selection-into-work and a selection-into-education correction using the log hourly gross wage as the dependent variable. Each column represents a separate regression. *HE* (*VOC*) implies that the estimation sample is based on individuals with a higher education (vocational training) degree. *UAS*=University of applied sciences degree.
Source: SOEP, own calculations.

Table A6: The tax function

Gross income/10^5	1.007***
	(0.00921)
Gross income^2/10^{10}	-1.160***
	(0.0161)
Gross income^3/10^{15}	0.506***
	(0.00900)
Gross income^4/10^{21}	-0.873***
	(0.0185)
Gross income^5/10^{28}	5.004***
	(0.120)
Married	-0.00877***
	(0.00123)
Number of children	-0.0112***
	(0.000514)
Constant	0.124***
	(0.00159)
N	47570

Notes: This table displays the results of linear regressions using the average tax rate as the dependent variable.
Source: SOEP, own calculations.

Table A7: Simulated life-time earnings (in thousand Euros), men

	No selection	Only work	Educ + work
HE, gross	1,427	1,366	1,181
HE, net	876	842	743
VOC, gross	1,249	1,208	1,086
VOC, net	785	764	700

Notes: This table displays the simulated mean life-time earnings of men for higher education and vocational training in prices of 2016. *HE*=Master degree, *VOC*=Vocational training degree, *Gross (net)* refers to gross (net) labor earnings.
Source: NEPS, SOEP, own calculations.

Table A8: Simulated life-time earnings (in thousand Euros), women

	No selection	Only work	Educ + work
HE, gross	923	901	907
HE, net	610	598	602
VOC, gross	725	722	726
VOC, net	510	508	511

Notes: This table displays the simulated mean life-time earnings of women for higher education and vocational training in prices of 2016. *HE*=Master degree, *VOC*=Vocational training degree, *Gross (net)* refers to gross (net) labor earnings.
Source: NEPS, SOEP, own calculations.

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