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Higher education funding in Germany
A distributional lifetime perspective

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Abstract

This paper analyzes higher education funding in Germany from a distributional perspective. For this, I first compare the quantitative importance of different funding instruments, from free tuition to subsidized health insurance for students. I show that free tuition is, by far, the most important instrument. Then, I take a lifetime perspective and assess how individuals of different expected lifetime incomes benefit from higher education funding. I distinguish between different fields of study as there are large differences in both the expected lifetime earnings of graduating from a specific field and the social cost of tuition associated with each field. Finally, I focus exclusively on the instrument of subsidized tuition and simulate the introduction of different tuition fee schemes with income-contingent loans. While the distributional effects would be sizable in absolute terms, I estimate that they would cause few individuals to change their educational decisions.

Keywords: Higher education, Education finance, Dynamic microsimulation
JEL classification: C53, I22, I23

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1 Introduction

Who should pay for higher education has been a controversial topic for decades. Some industrialized countries, such as as Britain, Australia, and the US commit students to pay a substantial share of the cost of tuition themselves. Countries such as France or Germany, in contrast, offer free or highly subsidized tuition and finance higher education mostly through taxes. In addition, countries also differ with respect to the presence of additional instruments of higher education financing, such as student loans and grants, and subsidized health insurance.

One main reason why the financing of higher education is a fundamentally controversial topic are the distributional concerns that go along with it. The literature which analyzes the distributional effects of higher education funding can be classified into "cross-sectional" and "longitudinal" studies. Cross-sectional studies analyze how higher education funding redistributes between households along the current income distribution. Naturally, households with students receive benefits from subsidized tuition while those without students do not. A substantial part of this literature analyzes the distributional impact of subsidized tuition by computing the benefits each household receives (see, for instance, Callan et al., 2008; and Koutsampelas and Tsakloglou, 2015). In contrast, some studies go further and compute net transfers by contrasting the received benefits with the taxes each households (implicitly) pays for higher education (Barbaro, 2002).[1]

While the cross-sectional perspective might deliver interesting insights into how higher education funding redistributes between households of different socio-economic status, it does not take into account the heterogeneous life courses of students and non-students. This is exemplified by the fact that in a cross-sectional perspective a substantial fraction of students who live outside their parental households are at the lower end of the income distribution. While potentially being classified as "poor" given their current living standard, students usually have a higher expected lifetime income than non-students. Analyses with a longitudinal perspective, in contrast, address the lifetime perspective of higher education funding. These studies focus on the current young cohort itself and analyze the distributional effect of higher education funding within this cohort (and between academics and non-academics, for instance).

Analogously to Barbaro (2002) in the cross-sectional perspective, Borgloh et al. (2008) compare the benefits young adults receive from higher education funding to the taxes they (implicitly) pay for higher education over the life cycle.[1] Dearden et al. (2008) analyze the distributional impact of a reform of the British higher education funding system. They focus on the subpopulation of students

[1]The assumption is that a fraction of an individual's tax payment is used to finance higher education. This fraction is assumed to be the same as the fraction higher education funding has on the total public expenditures.

and analyze how the reforms redistributed transfers between students of high and low lifetime income and of different parental income. Finally, studies such as Harding (1995) and Chapman and Sinning (2014) indirectly focus on the distributional effects of higher education funding in that they simulate individual tuition fee repayments over the life cycle.

However, these studies are the only recent studies with such a longitudinal focus I am aware of. Most likely, the reason for this scarcity are the data requirements: If researchers want to analyze the distributional effects of higher education funding within a young cohort, then the latter's life cycle needs to be forecasted. Borgloh et al. (2008), for instance, generate such life cycles by averaging individual earnings based on gender, age, and field of study. Harding (1995), in contrast, uses a dynamic microsimulation model developed for Australia (Harding, 1990).

In this paper, I apply a longitudinal perspective to analyze the distributional impact of higher education funding for a young cohort in Germany. To generate artificial life cycles, I use the dynamic microsimulation model developed in Fischer and Hügle (2020) and modify it for the purpose of this study. Dynamic Microsimulation has the advantage that it accounts for path dependencies in employment and family formation (such as marriage and fertility) and for cohort and time effects when forecasting life cycles. In addition, it provides an entire distribution of life cycles for each set of initial values.

Importantly, my analysis distinguishes between different fields of study. The reason is that both tuition cost and expected lifetime income vary considerably across these fields. Borgloh et al. (2008) is the only other study that distinguishes fields of study I am aware of. Due to data limitation, however, they had to impute the fields of study from the current occupation of an individual. Instead of this indirect measure, I use more recent data in which the field of study was directly surveyed.

The distributional analysis has three parts: In the first part, I analyze the current system of higher education funding and compare the quantitative importance of different funding instruments such as free tuition, student loans and grants, and subsidized health insurance. Then, I compare these benefits across fields of study. In the second part, I add the lifetime perspective to the analysis and show how different deciles of the lifetime income distribution financially benefit from higher education funding. Here, I focus on the individuals with a higher education entrance degree in Germany, i.e. those individuals who are usually confronted with the choice between higher education and vocational training. In the last part, I show the potential distributional consequences of an alternative system with tuition fees and income-contingent loans. A system with tuition fees and income-contingent loans implies that students receive loans to cover tuition fees and living cost while they are studying, but have to pay back (part of) their tuition cost over the life course if their income exceeds a certain threshold. Such systems have been in place in various Western countries, such as England, Australia, and New Zealand (Britton et al., 2019) and have also been discussed in Germany (see Lergetporer and Woessmann, 2019; and Chapman and Sinning, 2014).

I find that, while students benefit from multiple higher education funding instruments, free tuition is, by far, the quantitatively most important one. Due to the heterogeneity in the cost of tuition across fields of study, however, there is a large range in how much students benefit from free tuition. For instance, while students of medicine receive free tuition worth of about 160,000 Euros over the lifetime, students of humanities and the social sciences only receive about 20,000 Euros.

Focusing on the young adults with a higher education entrance degree, I find that the share of academics continuously increases across lifetime income deciles and hence higher deciles benefit more from higher education funding than lower deciles. At the same time, there is a large heterogeneity within the groups of academics and between fields of study. For instance, those with the highest expected lifetime incomes, students from the fields of medicine and math/natural sciences, are the ones who benefit most from higher education funding as their fields are particularly costly.

Finally, I show that the introduction of different tuition fee regimes with income-contingent loans would have little distributional consequences relative to net lifetime income. Consequentially, I estimate that the hypothetical tuition fee reforms analyzed in this study would barely distort the educational decisions of young adults.

The paper proceeds as follows. Section 2 explains the data sets used in the analysis. Section 3 describes the fields of study and the distributions of students over these fields. Section 4 explains the different instruments of higher education funding. Section 5 describes the approach of dynamic microsimulation. Results are presented in section 6 and section 7 concludes.

2 Data

In this study, I mainly rely on two data sets, the German Socio-Economic Panel (SOEP) and the National Educational Panel Study (NEPS). The SOEP is an annual, nationally representative longitudinal study of private households across Germany and currently surveys about 30,000 people in 15,000 households (Goebel et al., 2018). I use the SOEP primarily to estimate the dynamic microsimulation model (see Section 5), but partially also to compute the value of different instruments of higher education funding (see Section 4).

The NEPS (Blossfeld et al., 2011) is a longitudinal study that surveys individual educational trajectories, decisions, and competences. It has different starting cohorts, defined by the point in time the NEPS starts observing the cohort, from newborns to adults, and follows each of these cohorts along the life span. I draw on three of these starting cohorts (SC): SC4 (9th graders), SC5 (students), and SC6 (adults). Using these data sets, I estimate the shares of students in different educational paths (see Section 3), the values of different instruments of higher education funding (see Section 4), and the educational choice model to assess likely behavioral responses of tuition fee reforms (see Section 6).

3 Higher education in Germany: Fields of study and degrees

I follow Borgloh et al. (2008) and the Federal Statistical Office (Statistisches Bundesamt, 2020) and cluster all individual study programs (*Studiengänge*) into "fields of study" (*Studienbereiche*).[2] Table 1 lists these fields of study and gives examples of specific individual study programs that fall into each field.[3] Figure 1 describes the distribution of first-year students in 2018 over these fields. While almost

Table 1: Fields of study

Field of study	Examples of individual programs
Engineering	Mechanical eng., Electrical eng., architecture, computer sc.
Humanities	Philosophy, history, linguistics
Math and natural sciences	Mathematics, biology, chemistry, physics, geography
Medicine	Human medicine, dentistry, veterinary medicine
Social sciences	Economics, law, political science, sociology, psychology
Other	Agricultural sc., science of forestry, nutritional sc., sports, arts

Notes: This table displays the list of fields of study and examples of corresponding individual study programs. Note that for convenciency, I decided to use a shorter name for "social sciences" (*Rechts-, Wirtschafts-, und Sozialwissenschaften*) rather than translating the longer name the Federal Statistical Office uses.

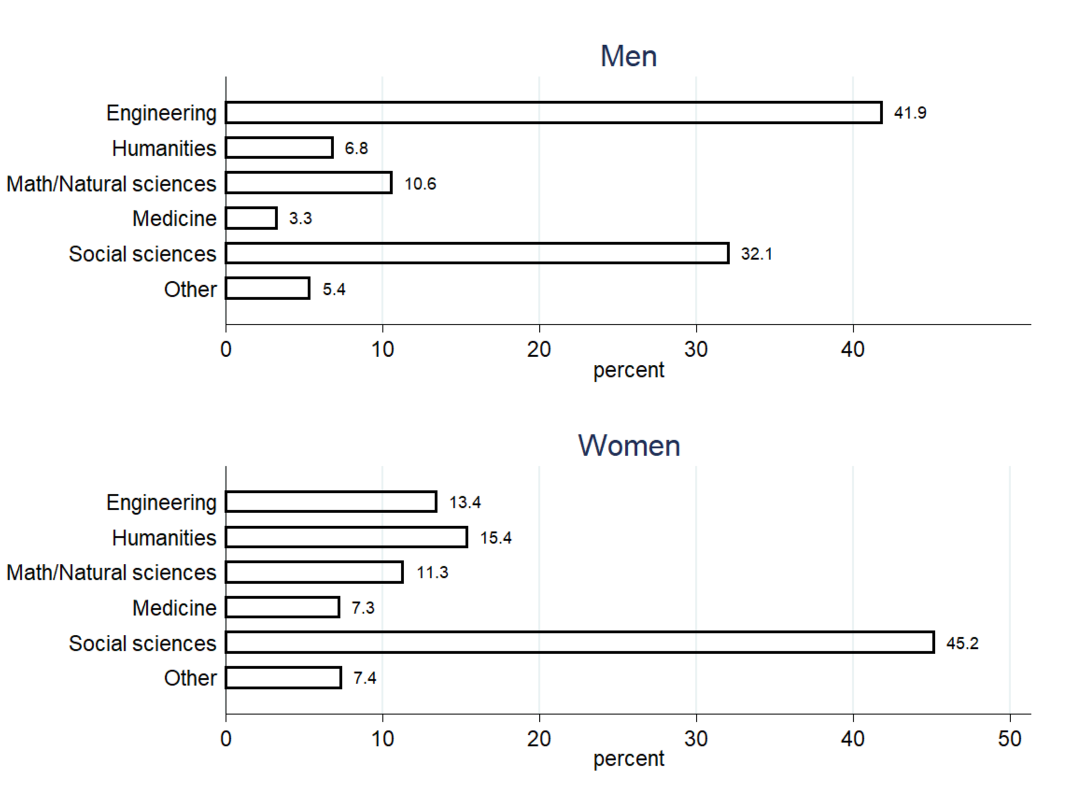
one half of all women (45%) are enrolled in the social sciences, only one third of men choose this field. In contrast, 42% of all men are enrolled in engineering, while for women this share is only about 13%.

Depending on the field of study, students can earn different degrees. As a consequence of the mid-2000 Bologna reforms, German higher education institutions now largely award bachelor and master degrees. In addition, some study programs still finish with state exams (*Staatsexamen*), such as medicine, law, and teacher training. As among the latter only medicine represents a field of study by itself, I assume for the analysis that studying the field of medicine leads to a state exam while in all other fields either a bachelor or a master degree is obtained. For these other fields, I estimate that the field-specific average share of students who leave the education system with a bachelor degree ranges from 11% (social sciences) to 21% (math/natural sciences).

[2] Note that I add sports and arts to the residual category of "other", while Borgloh et al. (2008) exclude these individual study programs.

[3] This level of aggregation was chosen as the SOEP would contain only a small number of observations for individual study programs and the Federal Statistical Office (Statistisches Bundesamt, 2020) only lists the tuition cost on this level of aggregation.

Figure 1: Distribution of academics over fields of study



Notes: The graphs display the distribution of first-year students in 2018 over fields of study by gender.
Source: Statistisches Bundesamt (2019), own calculations.

Apart from the earned degrees, there are two other dimensions on which heterogeneity between fields might be considered. The first is length of study. I therefore estimate the average study length until graduation for each field of study using the NEPS student cohort. I find that for all fields of study presented above, the average study length to obtain a master degree or a state exam is approximately 11 semesters. I therefore do not consider potential heterogeneity in study length between fields of study.[4]

A second dimension of potential heterogeneity is the risk of "dropout". It is a well-established fact that roughly about one third of bachelor students do not finish their studies. However, it is plausible to assume that a large fraction of these "dropouts" are just changing the study program, often within the same field of study, as defined above. In the latter case, "dropping out" just implies prolonging the length of study, while the student obtains a degree in the same field of study.[5] Yet, the frequency of these paths is difficult to assess with current data. Therefore, I ignore the risk of dropout.[6]

[4]For simplicity, I also ignore potential heterogeneity in study lengths within fields of study.

[5]An example would be a student who first enrols in mechanical engineering, then drops out and enrols afterwards in electrical engineering (i.e. another individual program within the same field of study.)

[6]However, using the relatively few field-specific dropout observations in the NEPS, I estimate that in all fields of study the share of dropouts who do not re-enter another study program is below 10%.

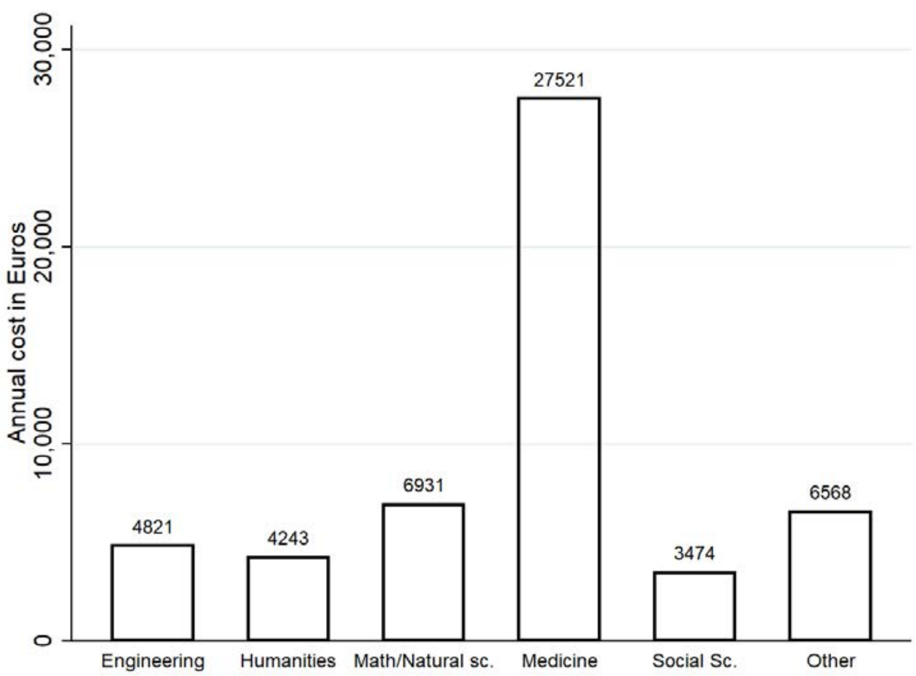
4 The instruments of higher education funding

In this section, I explain the different instruments of higher education funding in more detail. Using SOEP and NEPS data, I then estimate the monetary values of each instrument conditional on the field of study.

4.1 Free tuition

Currently, no German state collects tuition fees for the first degree, i.e. for the first bachelor and a consecutive master degree or a state exam.[7] Hence, the state incurs a sizable cost for each student. Figure 2 shows the cost of tuition per student and year. These costs can be calculated by using the costs for tuition and research reported by the Federal Statistical Office (Statistisches Bundesamt, 2018) and the so-called "coefficients for research and tuition" (*Forschungs- und Entwicklungskoeffizienten*) to subtract the cost associated with research activities. In terms of tuition cost, there is substantial heterogeneity across fields of study. With an annual cost of about 27,500 Euros, higher education places in medicine are, by far, the most expensive ones. In contrast, places in the social sciences cost only about 3,500 Euros per student and year.

Figure 2: Tuition cost by field of study



Notes: Costs are in prices of 2019. The costs can be calculated by using the costs for tuition and research reported by the Federal Statistical Office (Statistisches Bundesamt, 2018) and using the "coefficients for research and tuition" (*Forschungs- und Entwicklungskoeffizienten*) to subtract the cost associated with research activities.
Source: Statistisches Bundesamt (2018), own calculations.

[7] A few states collect fees in other cases, for instance for second degrees or for long-term students. I will ignore this here.

4.2 Student loans and grants (BAföG)

Apart from free tuition, a key feature of higher education funding in Germany is the provision of grants and loans through the *Bundesausbildungsförderungsgesetz* (henceforth *BAföG*). The amount of BAföG support a student has access to during the standard period of study depends on own and parental income and wealth and on whether the students lives in the parental household. Currently, the maximum monthly BAföG payment is 744 Euros (excluding supplements for insurance). Half of the BAföG payment is usually given as a grant, while the other half is provided as an interest-free loan. In 2016, 13.9% of all students received BAföG. Using the NEPS, I estimate the annual average BAföG payments given as a grant by field of study. I find that that there is only little heterogeneity between fields, with all fields of study having an average between 630 (engineering) and 775 Euros (other).

4.3 Child benefits

While their children are still in educational training and not older than 25, parents are entitled to child benefits. Currently, parents receive monthly 204 Euros for each of the first two children and slightly more for each additional child. As vocational trainees usually finish their education at a younger age than students, this implies that families of students receive child benefits for a longer time period. Assuming that parents transfer the received child benefits to their children, I assign each student a annual child benefit of 2,448 Euros (204 Euros/month · 12 months).

4.4 Health insurance

Students have different types of health insurances. Until the age of 25, they are usually covered by the public health insurance of their parents. If this is not the case, one alternative is the student health insurance with a reduced insurance contribution of currently 109 Euros per month. In addition, students might be compulsorily insured in the public health insurance, for instance, if they work more than 20 hours per week. Finally, some students are also privately insured.

I assume that only students who are either insured through their parents or who have a student health insurance are subsidized. To compute this benefit, I further assume that if students were not subsidized, they would be treated as individuals with low income who are part of the public health insurance. For the latter, the health care contribution rate of 14,6% is multiplied with the minimum assessment threshold, which is currently 1,062 Euros, equaling a contribution of 155 Euros. Hence, the benefit for individuals in the family insurance is 155 Euros, while the benefit of individuals in the student insurance is 46 Euros (155-109). Using the SOEP, I estimate the share of students in each type of health insurance and compute the weighted average of the health insurance subsidy. I find that, on average, students are subsidized by 1,228 Euros annually.

4.5 Education tax allowance

Another subsidy is the education tax allowance (*Ausbildungsfreibetrag*) which is currently 924 Euros per year. To receive this allowance, the student must live outside the parental household and be at most 25 years old. For simplicity, as the subsidy implied by the allowance is relatively small compared to other instruments, I assume that the parents of all students receive the allowance.

To estimate the average benefit of receiving the allowance, I use the SOEP and the current income tax formula and estimate the tax burden of adults in the age range 40-65 who live in the same household as students under two scenarios: with and without the allowance. I assume income tax splitting of couples and no further allowances. The difference in the tax burden is then the financial benefit due to the education tax allowance. I find that, on average, the allowance implies an annual benefit of 201 Euros per student.

4.6 Further instruments

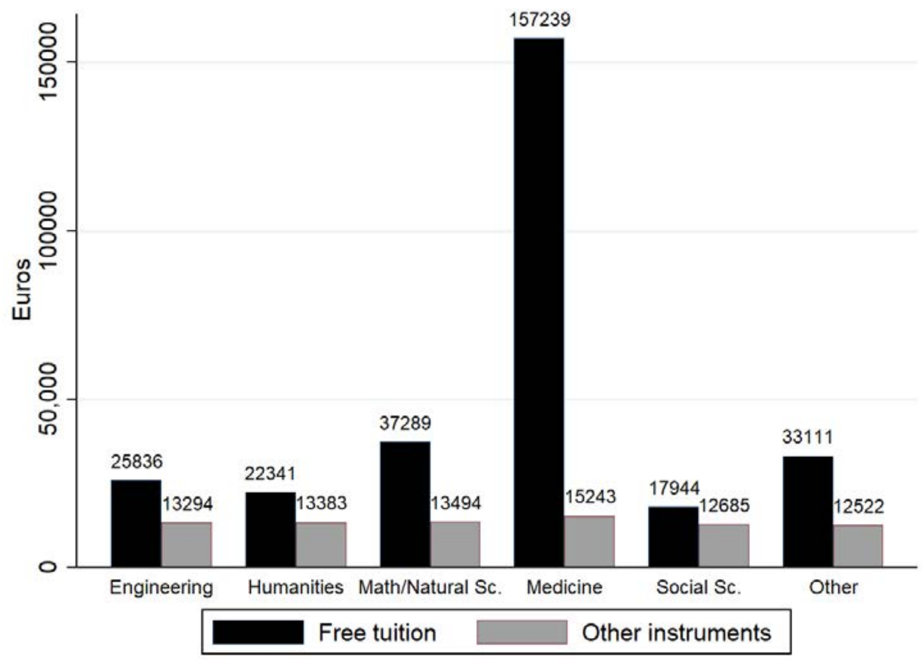
Further instruments of higher education funding include grants to organizations for the promotion of young talent (*Begabtenförderwerke*), the Germany scholarship (*Deutschlandstipendium*), funding of educational competitions, and student exchange programs. I sum up the amounts spent for these instruments and assign each student the average benefit of 235 Euros per year. I do not consider student housing promotion as there is no recent publicly available data on it.

Another potential instrument that might be taken into account are credit points for higher education in the calculation of civil service pensions (Borgloh et al., 2008). The idea is that for those academics who enter civil service, the years of studying can be counted as credit points. Importantly, however, a civil servant reaches the maximum rate of pension with 40 years of service. In the dynamic microsimulation model (explained in the next section) I assume that all academics enter the labor market at age 24 and retire at age 67. Hence, the academics who are simulated to enter civil service cannot count their study time as credit points.

4.7 The present value of higher education funding instruments

Finally, Figure 3 shows the present value of lifetime benefits by field of study, assuming a discount rate of 2% and a duration of academic training of six years. As vocational trainees also receive all funding instruments except free tuition, I follow Borgloh et al. (2008) and only consider these instruments for the last three years of academic training (assuming that vocational trainees have finished their training after three years). Free tuition is the quantitatively most important funding instrument. For medicine, its value accumulates to more than 150,000 Euros over the lifetime. For other fields, it is substantially smaller, ranging from less than 20,000 Euros (social sciences) to about 37,000 Euros (math/natural sciences). In contrast, the value of all other instruments considered jointly only amounts to about 13,000 Euros over the lifetime.

Figure 3: Lifetime benefits by field



Notes: The graph shows the present values of the higher education funding instruments by field of study in prices of 2019. "Other instruments" comprises the instruments student loans and grants (BAföG), child benefits, health insurance, education tax allowance and further instruments, as explained above. The instruments are explained in more detail in Section 4. The discount rate is 2%.
Source: SOEP, NEPS, own calculations.

The goal of the remainder of this paper is to analyze who receives these benefits in terms of expected lifetime income quantiles. Thereby, I will focus on the individuals with a higher education entrance degree who face the choice between taking up academic or vocational training. The next section explains how their life cycles are simulated.

5 Dynamic microsimulation

5.1 Simulating the lives of a young cohort

A key challenge to assess the distributional effects of higher education funding in longitudinal studies is the generation of life cycles. For this purpose, I use the dynamic microsimulation model outlined in

Fischer and Hügle (2020). In contrast to short-cut approaches which rely on cross-sectional data, a dynamic microsimulation model has the advantage of disentangling time and cohort effects when projecting life cycles from past observations. In addition, such models are able capture path dependencies and can thereby model heterogeneous life cycles.

The model simulates life cycles for the 1980s cohort in terms of wages, employment, and household formation (fertility, marriage, and divorce) from age 18 to 67 (the official retirement age in Germany). While there is an obvious mechanic link between wages, employment, and lifetime earnings, the processes of fertility, marriage, and divorce impact employment decisions of individuals and hence, ultimately, also lifetime earnings. Simulating the life courses of the 1980s cohort serves two purposes: First, important life cycle events such as labor market entry, births, and marriages can already be observed for this cohort. And second, the 1980s cohort is young enough to argue that its life courses are a plausible benchmark for a younger cohort which is about to enter higher education or vocational training.

In total, I simulate the life course of 500,000 individuals.[8] As in Fischer and Hügle (2020), each individual is assigned one of four general post-secondary educational categories: No post-secondary degree, a vocational degree without a higher education entrance degree, a vocational degree with a higher education entrance degree, and a higher education degree. While the analysis focuses on the individuals with a higher education entrance degree, individuals of the other two educational categories serve as potential spouses in the simulation.

The distribution of post-secondary education levels in the simulation matches the one reported in the Mikrozensus for the highest educational degrees of the 1982–87 birth cohort.[9] Figure 4 describes this educational distribution. The individuals with higher education are then further assigned a field of study and either a bachelor degree, a master degree (or a state exam in case of being assigned the field of medicine).[10] The distribution of fields of study within the group of academics follows the one described in Figure 1. It is assumed that students study for six years if they leave the education system with a master degree or a state exam and three years if they only obtain a bachelor degree. Vocational training also has a duration of three years.

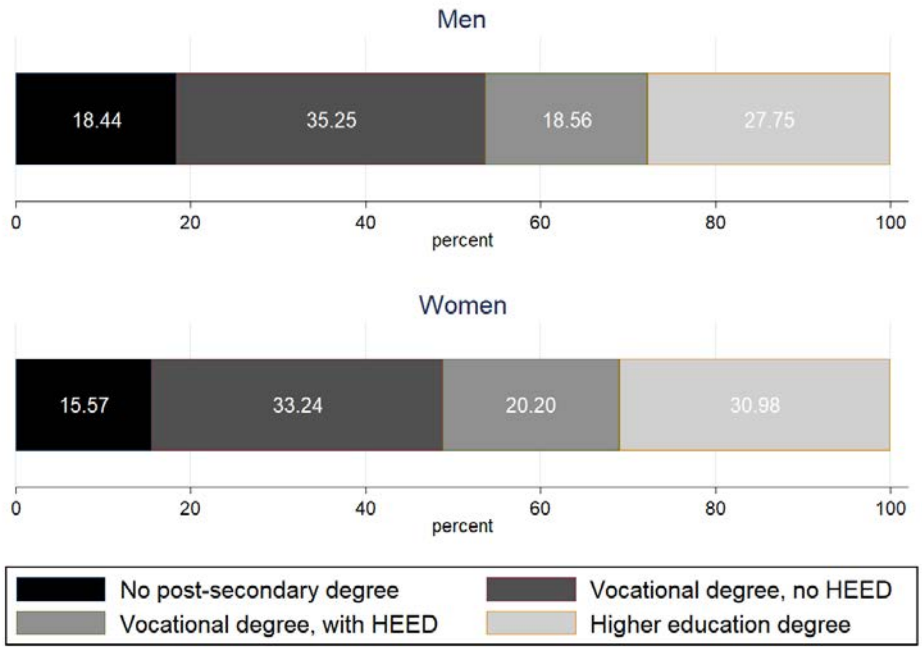
Hence, there are two levels of aggregation: A more aggregated level of post-secondary education levels which, in particular, distinguishes vocational degrees and higher education, and a more disaggregated level within higher education, which distinguishes field of studies and bachelor/master degrees.

[8] Due to computational reasons, I simulate 100 runs with 5,000 individuals and pool them for the distributional analysis.

[9] The empirical distribution on which we base our simulation comes from German *Mikrozensus* data (see Statistisches Bundesamt, 2018, for details).

[10] From now on, I will also refer to state exams by the term *master degree*.

Figure 4: Distribution of post-secondary education levels



Notes: The bars show the distribution of post-secondary education levels in the cohort 1982–1987 by gender. "HEED"= Higher education entrance degree.
Source: Statistisches Bundesamt (2018), own calculations.

For the modeling of transitions in employment and household formation (fertility, marriage, and divorce), I use only the more aggregated level. This implies that I assume that academics follow the same expected patterns, independently of their field of study or whether they only obtained a bachelor degree.[11] For the modeling of wages, however, I differentiate further into bachelor and master degrees, and different fields of study. This means that I allow for different wage profiles between academics depending on their field of study and bachelor/master degrees. The dynamic microsimulation model proceeds in three stages: Parameter estimation, life-cycle simulation, and tax-transfer simulation. In the following, each stage is described in more detail (for additional information see Fischer and Hügle, 2020).

5.1.1 Parameter estimation

The objective of this part of the dynamic microsimulation model is to estimate parameters that can then be used to simulate life cycles. More precisely, I estimate transition probabilities for household formation (marriage, divorce, and fertility) and employment categories, hourly wage regressions, and aggregate cohort-specific targets for household formation and employment.

The transition probabilities for household formation and employment are estimated by discrete-

[11] With the only difference being that bachelor graduates who do not continue to a master program enter the labor market earlier.

choice models and include dummies for the post-secondary education levels or indicators for being in academic and vocational training, indicators for migration background, age polynomials and different sets of variables that capture past employment biographies and past life-cycle events such as births, marriages, and divorces. All models are estimated separately by gender.

For marriage, I use two processes: First, the marriage probability is modeled estimating a binary logit model for all unmarried individuals. Second, in order to account for educational assortative mating, the individuals which were simulated to marry in the first process are matched based on an empirically observed matrix of marriage frequencies across the four post-secondary education levels. Divorce is estimated using a binary choice model on the household level. Finally, the probability of giving birth is estimated separately for married and unmarried women.

Employment is modeled as a three-step process: First, I use a binary logit model to estimate the probability of individual labor force participation. Second, I estimate a binary choice model for involuntary unemployment conditional on labor force participation. Third, multinomial logit models are used to estimate the probability of choosing specific working hours categories. For women, I distinguish five hours categories: Marginal employment (0-14 weekly working hours), reduced part-time work (15-24 hours), extended part-time (25-34 hours), full-time (35-42 hours), and over-time work (more than 42 hours). For men, I model three employment hours categories: Part-time (0-34 hours), full-time (35-42 hours), and over-time work (more than 42 hours).[12]

In the wage estimations, I regress individual log gross hourly wages on fourth-order polynomials of age, experience, and tenure, an indicator for migration background, orthogonalized indicators for federal states and year dummies separately by gender and post-secondary education level. Compared to the specification used in Fischer and Hügle (2020), I modify the regression for higher education graduates and include field of study and bachelor degree dummies. This ensures that wage differences across fields of study and a potential wage penalty of bachelor compared to master degrees are captured. Table A1 in the Appendix present the coefficient estimates. For the group of academics, I find a bachelor penalty of about 16% for women and 13.5% for men. As to the fields of study, I find large wage premiums of approximately 36-42% for studying medicine relative to study programs in the residual category "other" (the base category). Studying humanities, in contrast, only results in a 2-7% premium relative to this base category.

Finally, I estimate a set of aggregate cohort-specific targets for employment and household formation. This so-called *alignment* ensures that in the aggregate, the simulated transitions meet some projected trend. To estimate these targets I use binary and multinomial fractional regression models.

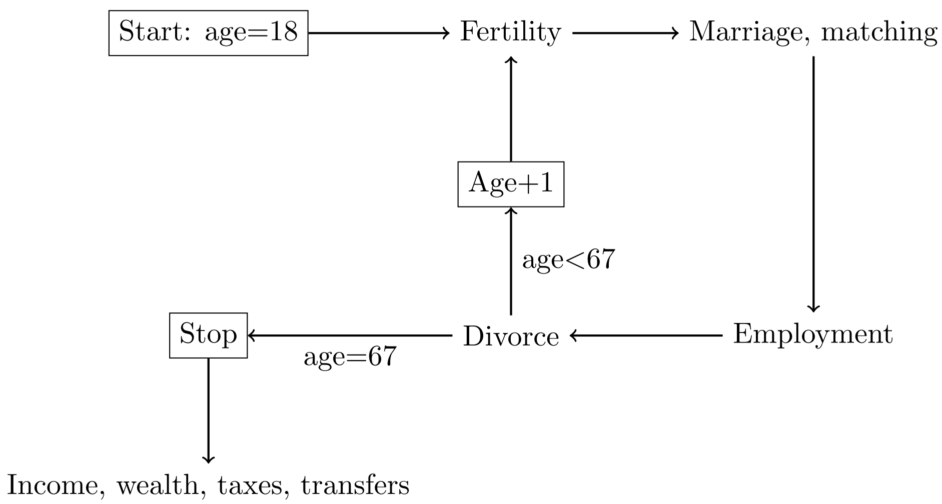
[12] In addition, I account for the particularities of labor market entry by modeling separate transitions for each of the first five years after graduation.

All models include polynomials of age and generational trends (generational trend is defined as *birth year* - 1930) in order to capture cohort effects, and control for the overall unemployment rate. Using the coefficient estimates, I predict age-specific target rates in employment and household formation for the 1980s cohort over the life cycle.[13]

5.1.2 Life-cycle simulation

In the simulation stage, I use the estimated parameters and the projected aggregate targets from the estimation stage and simulate the cohort's life cycle. Starting at age 18, the individual age is updated year-by-year and the transitions in employment and household formation are simulated as described in Figure 5. More precisely, the procedure to select individuals for transitions (fertility, marriage,

Figure 5: The simulation stage



employment, and divorce) works as follows:

1. Predict individual transition probabilities using the parameter estimates from the transition models.

2. Multiply each probability with a random draw from the unit interval.

3. Rank individuals according to these modified probabilities.

4. Based on this ranking, select individuals for transitions until the respective aggregate target rates are met.

After having simulated the transitions in employment and household formation, I can simulate the hourly wages. In order to align the variance of simulated wages to the variance of observed wages,

[13]The results of the transition models and the target estimation for employment and household formation are the same as presented in Fischer and Hügle (2020).

individuals are assigned log wage residuals conditional on gender and education, which are added to the predicted log wages. Exponentiating this sum then results in the the predicted hourly wages.[14] Finally, to obtain labor earnings hourly wages are multiplied with the level of working hours given the simulated employment category.

5.1.3 Tax-and-transfer simulation

In order to translate the simulated gross labor earnings into disposable incomes, I use the modified version of the STSM as described in Fischer and Hügle (2020). The STSM is a module that describes the main features of the German tax-transfer regime. Using the rules of the tax-transfer regime as of 2019 and given the simulated life cycles, I compute taxes, transfers, and social security contributions. To compute taxable income, I take into account the simulated incomes from dependent employment and self-employment. In addition, I assume that individuals accumulate savings according to age-specific savings rates as estimated by Brenke and Pfannkuche (2018). Furthermore, I assume that married individuals file for joint taxation and that couples split taxes according to tax class IV/IV and the so-called factor method (*Faktorverfahren*). As to social security contributions, I consider contributions to health, long-term care, and unemployment insurance but not to the pension system.[15] Finally, I simulate unemployment benefits, parental leave allowances, social assistance, housing benefits, child benefits, and additional child benefits at the household level.

6 Results

6.1 Simulated lifetime incomes

Figure 6 plots the average simulated individual gross and net lifetime incomes by field of study (including vocational degrees with higher education entrance degree).[16] The differences in lifetime incomes between fields of study essentially result from the differences in simulated hourly wages.[17] The rankings of fields in terms of lifetime earnings are similar for men and women. For both men and women, the average lifetime incomes of medicine graduates exceed those of other disciplines by far.

Male medicine graduates have, on average, discounted gross earnings of more than 2 million Euros

[14]Hence, the hourly gross wage of individual i is calculated as $\hat{w}_i = exp(x_i'\hat{\beta})exp(\hat{u}_i) = exp(x_i'\hat{\beta} + \hat{u}_i)$ where x is a vector of covariates, $\hat{\beta}$ is a vector of coefficient estimates, and u_i is a randomly drawn residual from the log wage regression conditional on gender and education.

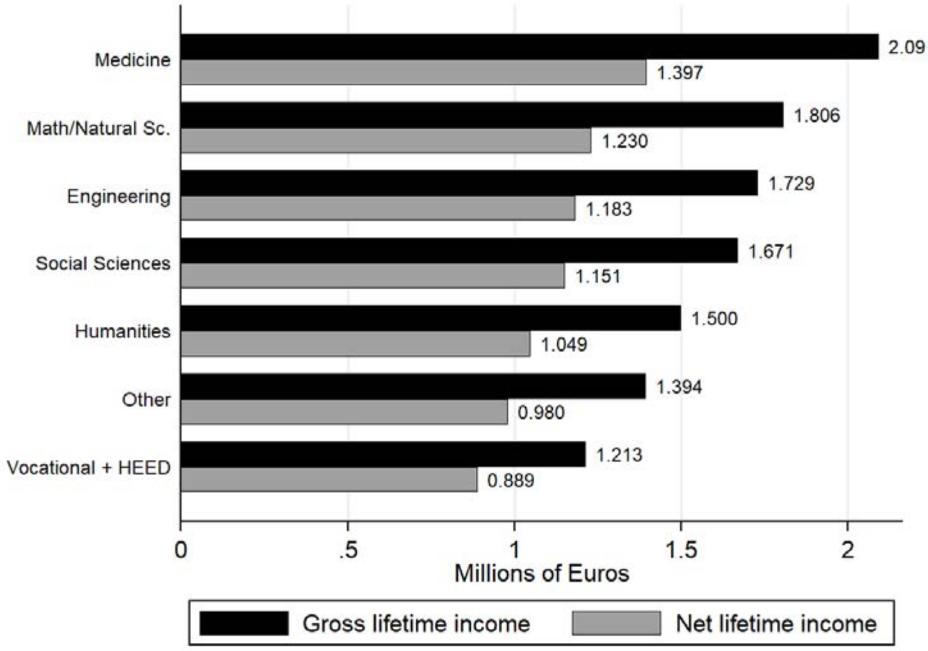
[15]Modeling the details of the pension system and pension-related transitions is beyond the scope of this study. However, pension entitlements are generally equivalent to the contributions paid.

[16]Importantly, I assume that married individuals file for joint taxation (as explained in Section 5.1.3) but do not pool their individual net incomes.

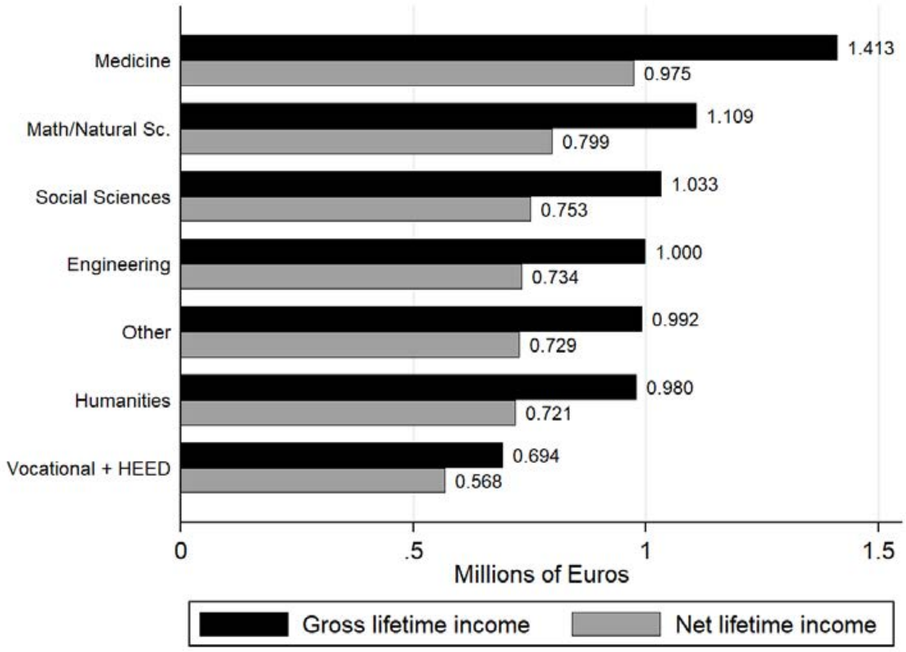
[17]Figures A1-A4 in the Appendix depict the simulated average hourly wages and annual earnings over the life cycle by field of study and gender.

Figure 6: Average simulated gross and net lifetime incomes by field of study and gender.

(a) Men



(b) Women



Notes: The figure depicts simulated individual gross and net lifetime incomes by field of study and education level in prices of 2019. Panel (a) shows the results for men, panel (b) shows the results for women. "Gross lifetime income" refers to the present value of annual gross income, discounted at 2%. Similarly, "net lifetime income" refers to the present value of annual net income, accounting for taxes, transfers, and social security contributions, discounted at 2%. I assume that individuals do not pool their incomes with their partners but that married couples file for joint taxation. "HEED"= higher education entrance degree.
Source: Own simulations.

over the lifetime, while female medicine graduates earn about 1.4 million. The tax-and-transfer system reduces these earnings to about 1.4 million Euros for men and 1 million for women. Individuals with degrees in the field of math and natural sciences are second in this ranking with male graduates earning about 1.8 million and female graduates accumulating 1.1 million. While for men, engineers earn substantially more than men in the remaining fields, for women there is no clear ranking. Finally, on average individuals with vocational degrees earn less than graduates of all fields of study with men earning about 1.2 million and women approximately 0.7 million.[18][19]

Finally, one can set the net financial burden of taxes and contributions paid minus transfers received over the life cycle into perspective by comparing them with the lifetime subsidies received from higher education funding (as analyzed in Section 4). Figure 7 shows the amount of higher education funding relative to the taxes and contributions paid (minus transfers received) over the life cycle. Both male and female medicine graduates benefit the most from higher education funding, even relative to the taxes and contributions they pay over the life cycle. Graduates of programs from the residual "other" category are second in this ranking which is due to their relatively costly tuition (compared to the remaining fields) and to their relatively low amount of taxes paid. Beyond the heterogeneity across fields, the graph also shows that women benefit much more from higher education funding when compared to the taxes and contributions they pay, even though the absolute amount of funding (conditional on field of study) is assumed to be the same for men and women.[20]

6.2 The current system: Benefits by lifetime income

Having estimated gross and net lifetime incomes for all individuals in the cohort, we can now analyze how individuals of different lifetime income quantiles benefit from the higher education funding instruments. Importantly, I condition on a higher education entrance degree in this analysis. Figure 8 plots the value of the funding instruments across net lifetime income deciles.

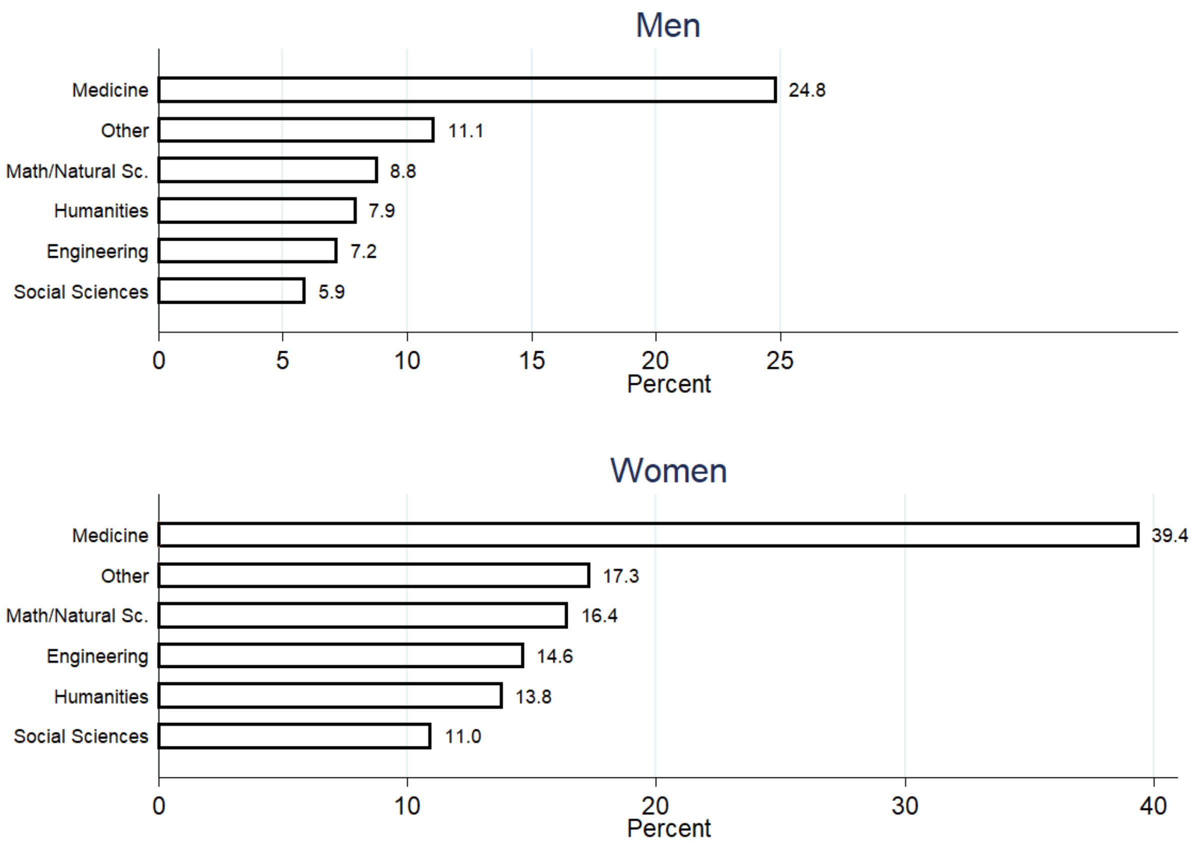
As expected, the value of all instruments considered jointly increases with decile. While for men (women), the lowest decile benefits from higher education funding by about 15,000 (slightly less than 20,000) Euros, the highest decile receives about 40,000 (50,000) Euros. One main reason is that the higher the decile, the larger (approximately) the share of academics who benefit from these funding

[18] The gross lifetime income gap between men and women could be decomposed into two factors: The differences in hourly wages (as shown in Figures A1 and A2 in the Appendix) and differences in the hours worked over the life cycle. While men with a vocational or academic degree are simulated to work around 80,000 hours over the life cycle, women with either a vocational or an academic degree are simulated to work around 60,000 hours.

[19] For the sake of clarity, I do not show here the profiles of the two other educational groups: No post-secondary degree and vocational degree without higher education entrance degree. The profiles of these groups are below the one for vocational training with higher education entrance degree.

[20] As argued above, to compare the subsidies received from higher education funding with the taxes paid used for the financing of higher education, one would need to make an assumption concerning the share of taxes that is used to finance higher education.

Figure 7: Higher education funding relative to taxes and contributions paid over the life cycle



Notes: The graphs display the amount of higher education funding received relative to the taxes and social security contributions paid (minus transfers) by fields of study and gender.
Source: Own calculations.

instruments. Figure 9 shows how the share of academics evolves across deciles. For both men and women, the share of academics increases from about 40 percent in the bottom decile to more than 80 percent in the top decile.

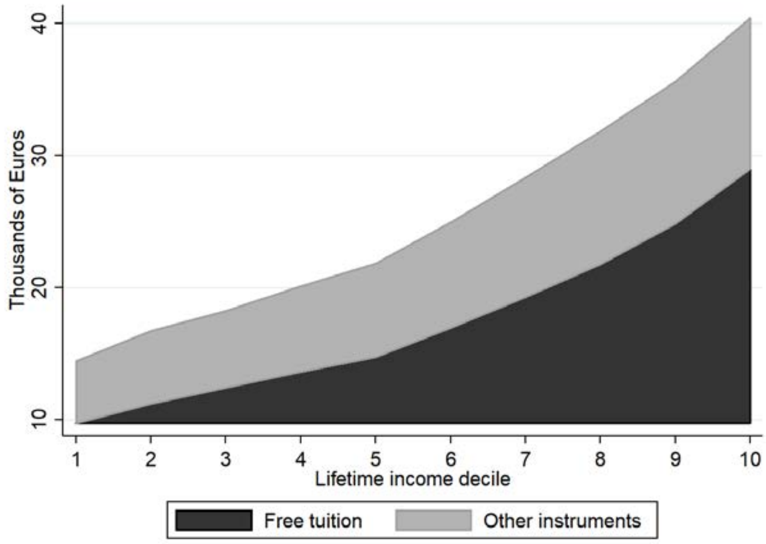
A second reason for the increase in benefits across deciles is the composition of fields of study within the group of academics. The higher the decile, the larger the share of graduates from both medicine and math/natural sciences, the two most costly fields of study. Finally, the fact that the increase in benefits across deciles is steeper for women than for men can be explained by the fact that the share of medicine students is more than double for women (7.3%) compared to men (3.3%) (as was shown in Figure 1).

6.3 Simulation of an alternative tuition fee/ICL system

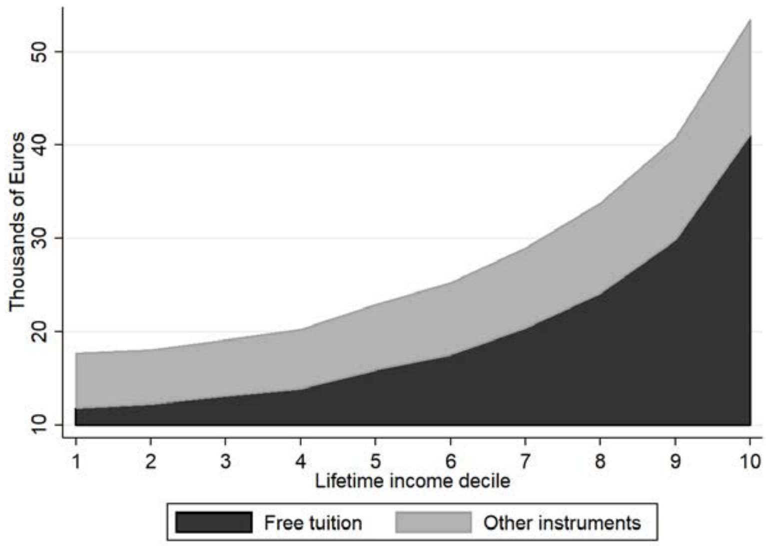
In this section, I will analyze a simulation of an alternative tuition fee system with income-contingent loans (ICLs). Tuition fees with ICLs mean that students gradually pay back (part of) the cost of

Figure 8: Benefits by net lifetime income decile

(a) Men

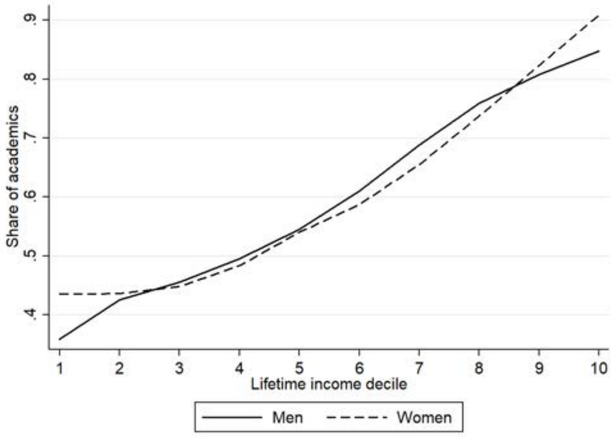


(b) Women



Notes: The figure depicts the present values of the individual higher education funding instruments by net lifetime income decile. "Other instruments" comprises the instruments student loans and grants (BAföG), child benefits, health insurance, education tax allowance and further instruments, as explained above. For further information about the individual instruments, see section 4. Panel (a) shows the results for men, panel (b) shows the results for women.
Source: Own simulations.

Figure 9: Share of academics by net lifetime income decile



Notes: The figure depicts the share of academics by net lifetime income decile for men and women.
Source: Own simulations.

tuition after graduation, given that their income exceeds a defined threshold. ICLs exist in various industrialized countries, such as England, Australia, and New Zealand and there is a vast heterogeneity in the systems' characteristics (see Britton et al., 2019, for a survey of these differences).

I consider such a system rather than a system with up-front payments as implemented in the mid-2000s in Germany since several authors have emphasized the advantage of deferred income-contingent payments in terms of efficiency and equity (see, for instance, Barr, 2004, and Chapman, 2006): ICLs may, for instance, reduce the risk of liquidity constraints for prospective students. As individuals from low-income parental households are more likely to encounter such liquidity constraints, ICLs may also be favorable in terms of intergenerational mobility. Furthermore, societal support seems to be larger for tuition fees with ICLs than for tuition fees with up-front payments: Using survey experiments for Germany, Lergetporer and Woessmann (2019) find that designing tuition fees as deferred income-contingent payments as opposed to up-front payments would considerably increase the support for fees (and indeed create a strong majority favoring the existence of tuition fees in general).[21]

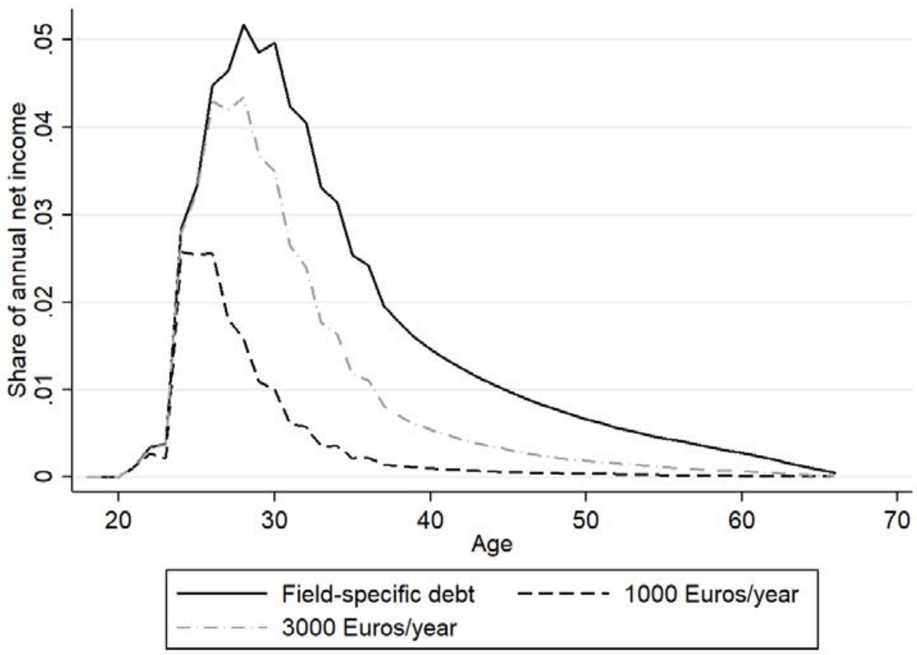
For simplicity, I consider a straightforward repayment scheme where the individual net income threshold is set to be 20,000 Euros and the repayment rate is 20% of marginal income, i.e. the individual net income above the threshold. I further assume that there is no interest rate. In terms of the size of tuition fees to be paid I consider three different levels: (i) 1000 Euros per year, (ii) 3000 Euros per year, and (iii) tuition fees that equal the full cost of each field of study. The level of the first scheme is comparable to the tuition fees that were introduced in the mid-2000s in Germany. The key difference is that in the ICL system tuition fees would not have to be paid instantaneously, but only

[21]The literature also discusses other potential systems of tuition fees and repayment such as simple loan systems where repayment is not contingent on income or graduate taxes. I will not consider these instruments here.

after graduation and only if earned income is sufficiently high. While the third scheme might seem extreme, it gives an idea about the (maximum) range of possibilities for tuition fees. At the same time, the debt levels accumulated under the third scheme correspond to the free tuition benefits (as shown in Figure 3).

Figure 10 shows the simulated average repayment schedules, as a share of annual net income, over the life cycle (pooled for men and women). It distinguishes between the three tuition schemes considered before (1,000 Euros, 3,000 Euros, and field-specific fees). Naturally, the larger the initial debt level, the larger the repayments by a given age and the longer the repayment duration. Hence, while on average tuition fees of 1,000 Euros per year would imply a repayment maximum of about 2.5%, field-specific tuition fees would cause average repayments of up to 5% of net income in a given year. In addition, while under the 1000-Euros fee individuals have paid back almost the whole debt before age 40, field-specific fees would imply that repayment has to continue until around retirement.

Figure 10: Simulated repayment schedules over the life cycle



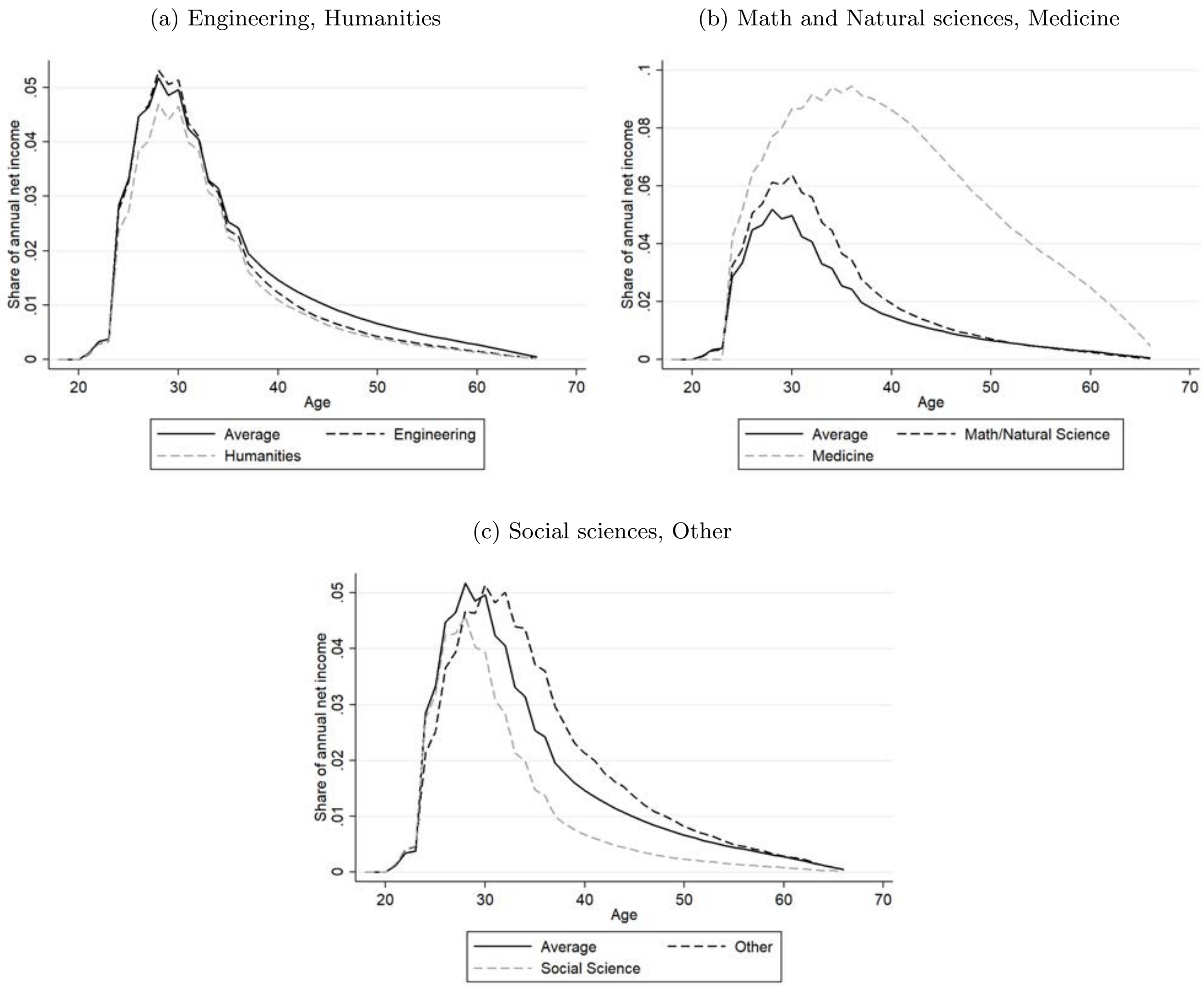
Notes: The figure shows the average simulated repayment schedules for the different tuition schemes over the life cycle. To compute the field-specific average, men and women are pooled with a weight of 50% each.
Source: Own simulations.

Figure 11 shows the average repayment schedule of each field under field-specific fees. It becomes clear that there would be substantial heterogeneity across fields of study. Most notably would graduates of medicine face repayments that are much larger than the profiles of graduates from other disciplines.[22] The graduates of mathematics and natural sciences have the second highest repayment

[22]It should be noted here, that there is also a substantial difference in repayment schedules for medicine between

burden in young ages being a result of their relatively large cost of tuition and their high expected earnings. Interestingly, despite having a similar cost of tuition, graduates of the residual category "other" have a below-average relative repayment when young but do have to continue repaying more towards older ages. The reason is that they have much lower projected earnings over the life cycle.

Figure 11: Simulated repayment schedules over the life cycle



Notes: The figure shows the average simulated repayment schedules for field-specific tuition fees over the life cycle. Each panel shows the repayment schedule of two fields of study and the average over all fields for comparison. To compute the field-specific average, men and women are pooled with a weight of 50% each.
Source: Own simulations.

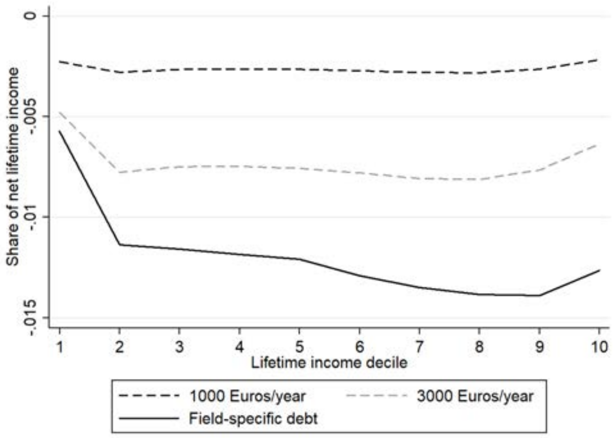
Finally, Figure 12 shows the distributional effects of changing from the current system without tuition fees to one of the tuition fee and ICL systems described above. Naturally, the system with 1,000 Euros per year would have the lowest distributional impact. Here, the share of the net lifetime income spent for tuition would be below 0.5% for all deciles. The curve for field-specific tuition fees is essentially mirroring the area for free tuition in Figure 8 where the value of the higher education

men and women. As male medicine graduates have much higher net earnings, they pay off their debt much earlier. Consequentially, the fact that repayment continues until around retirement is mainly driven by women.

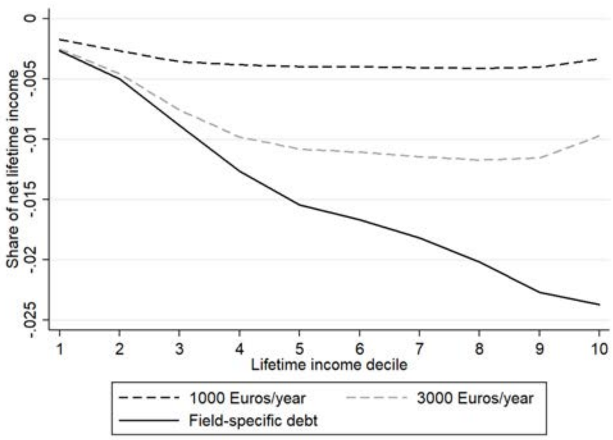
funding instruments was plotted against lifetime income deciles (in absolute terms).[23] The negative distributional effect increases across deciles, again being a result of both the increasing share of academics and the changing composition of the different fields of study within each decile. However, the share of net lifetime income spent on tuition would be small even for the highest deciles, reaching a maximum of less than 1.5% for men and less than 2.5% for women. The gender difference is mainly due to the fact that female graduates have a much lower projected net lifetime income and hence debt is larger relative to lifetime income. In addition, the gender difference in the distributional effects for the top deciles can be explained by the share of medicine graduates (which is more than double for women compared to men).

Figure 12: Simulated distributional effects of a tuition fee/ICL system

(a) Men



(b) Women



Notes: The figure depicts the distributional effects of the three different tuition fee schemes described above, without lump-sum redistribution of the revenue from paid tuition. Panel (a) presents the results for men, while panel (b) the ones for women.
Source: Own simulations.

[23] The only difference is that not all individuals pay back their full debt over the life cycle.

6.4 Behavioral responses

In order to assess the likely behavioral effects of the hypothetical tuition fee reforms described above, I estimate a Conditional Logit model. This model is a modified version of the one used in Hügle (2020) where the decision to enrol in higher education is estimated as a binary choice between higher education and vocational training. Here, I assume that the individuals with a higher education entrance degree can choose between different fields of study and vocational training.[24]

I assume that individuals associate a level of utility with each educational path (comprising all fields of study plus vocational training), such that:

$$U_{ij} = x'_{ij}\beta + \varepsilon_{ij},\ j = 1, ..., J.$$

where U_{ij} is the utility level individual i associates with educational path j, x_{ij} describes the characteristics and attributes of individual i and alternative j, and ε is the error term. Most importantly, x contains individual i's simulated individual net lifetime income under alternative j. To simulate lifetime incomes I use again the dynamic microsimulation model described above and estimate slightly modified wage regressions interacting the fields of study with dummies for the German states creating regional variation in net lifetime incomes. In addition, x contains variables for parental education, parental occupation, migration, a measure for cognitive skills, and gender as control variables.[25] Assuming that ε_{ij} is i.i.d. EV(1) distributed, the probability that i chooses j is:

$$P(y_i = j) = \frac{exp(x'_{ij}\beta)}{exp(x'_{i1}\beta) + ... + exp(x'_{iJ}\beta)},\ j = 1, ..., J.$$

I use the NEPS SC4 (9th graders) data set to estimate the model. Table A2 in the Appendix presents the Conditional Logit coefficient estimates. Table A3 shows the results from using the estimation sample to simulate changes in net lifetime income separately by field of study (including vocational training). I find elasticities in the range of 0.4–0.8, i.e. a 10% increase in the expected net lifetime income in field j, ceteris paribus, increases the average choice probability of this field by 4–8%. The literature on the elasticity of field choice with respect to expected income has produced a large range of estimates (see, for instance, the survey paper by Altonji et al., 2016). An elasticity of 0.6, for instance, appears to be rather in the upper part of those estimates.[26]

Figure 13 shows the average predicted probabilities under the different tuition schemes for the

[24] For those individuals with a higher education entrance degree, vocational training usually is the only attractive alternative to higher education.

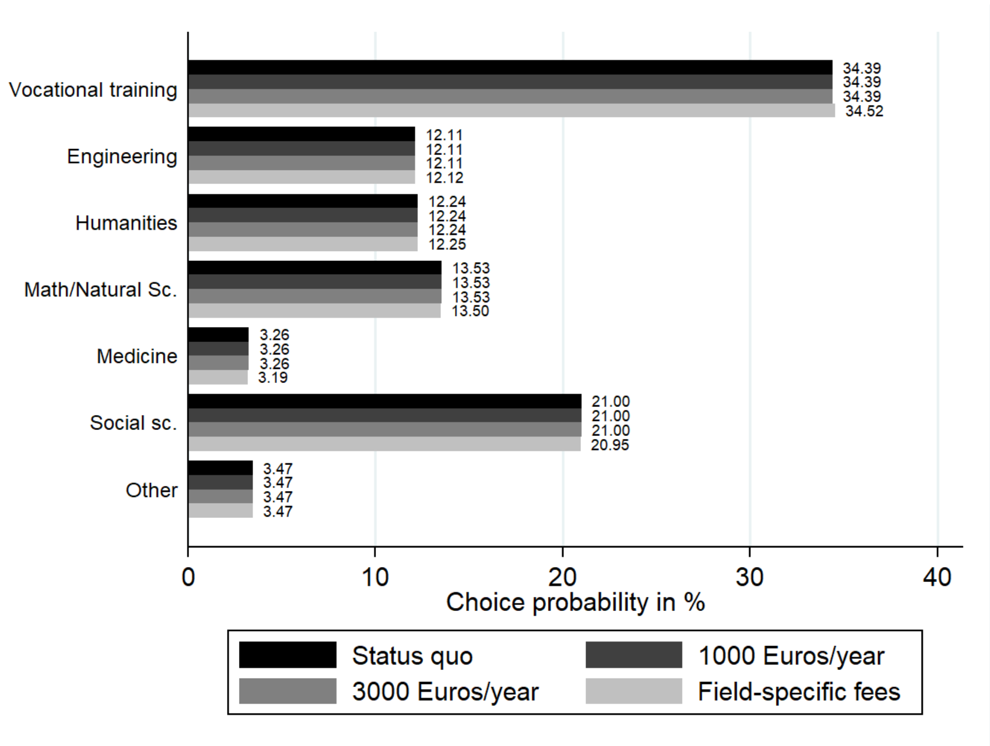
[25] These variables were interacted with alternative-specific dummies to make them varying over alternatives.

[26] Recent estimates range from 0.01 (Beffy et al., 2012) to 0.67 (Long et al., 2015).

NEPS sample. In general, only marginal changes can be found. For the ICL schemes with tuition fees of 1,000 or 3,000 Euros annually, there are almost no changes. In addition, even for field-specific fees, responses are quite small. The average predicted probability to choose medicine, whose students would be financially affected most strongly by field-specific fees, would only drop from 3.26% to 3.19%.

The main reason these predicted changes are so small is that while the redistribution implied by the proposed tuition fee reforms may appear large in its absolute size it is minor in terms of net lifetime income (as shown above). Clearly, the ICL scheme with fees that fully cover the cost of tuition are an extreme case. For alternative schemes that lie closer to the 1,000 and 3,000 Euro schemes, the model would predict almost no behavioral responses.

Figure 13: Behavioral responses to the introduction of different types of tuition fees



Notes: The graph shows the average predicted choice probabilities for the estimation sample using the Conditional Logit estimates as presented in A2 in the Appendix. "Status quo" is the current system without tuition fees. "1,000 (3,000) Euros/year" refer to the tuition fee scheme with a tuition level of 1,000 (3,000) euros annually. Finally, "Field-specific fees" is the tuition scheme were tuition fees equal the full cost of tuition.
Source: SOEP, NEPS, own calculations.

7 Conclusion and discussion

This paper analyzes the instruments of higher education funding from a distributional perspective. In the first part, I assess the quantitative importance of different funding instruments for different fields of study. I find that free tuition is the most important instrument with a present value between 20,000 and close to 160,000 Euros depending on the field of study. In the second part, I simulate the life cycles of a young cohort in order to analyze who benefits from higher education funding in terms of expected lifetime income. I show that the benefit from higher education funding is increasing by decile, being a result of the increasing share of academics and the composition of different fields of study in higher deciles. In the third part, I analyze the distributional consequences of different hypothetical tuition fee schemes. I find that they would imply almost no behavioral responses in terms of the field choice. The reason is that the redistribution implied by the hypothetical reforms is only marginal relative to net lifetime income.

Differentiating between fields of study proved fruitful due to their differences in tuition cost and expected lifetime incomes of their graduates. Yet, a more detailed analysis would be important, as there is still sizable heterogeneity in earnings within the fields of study as defined here. However, there is a lack of panel data with a larger amount of observations for such individual study programs (*Studiengänge*). As such data becomes available, it might be worthwhile to differentiate further within fields of study. Furthermore, with a larger amount of panel data available, one could account for field-specific employment and household transitions.

Fields of study also differ substantially in the share of their graduates who become self-employed. On the one hand, I account for this fact when computing social security contributions through the tax-and-transfer simulation. On the other hand, I do not consider the fact that self-employed academics, for instance physicians with a medical practice, often have a sizable investment early in their careers and then rely on this investment as a retirement provision in later years.[27] While the dynamic microsimlation model used in this paper models some general form of age-specific savings, future research could include savings, investment, and (in a more detailed way) capital income that depend on the field of study.

On a more general level, future research could also connect the two main approaches in the analysis of the distributional effects of higher education funding, the cross-sectional and the longitudinal approach. More specifically, the longitudinal approach could be extended by connecting the individuals of the young cohort, whose life cycles are being forecasted, with the parental generation. This would essentially be a contribution to the field of intergenerational mobility.

Finally, it is necessary to put the analysis into the perspective of education funding in general: While the analysis of this paper shows the importance of different higher education funding instruments and who benefits from these instruments, it should be taken into account that individuals in post-

[27] Using German microcensus data for the years 2005 to 2009, Glocker and Storck (2014), for instance, calculate that about 93% of all individuals with a PhD in dentistry are self-employed.

secondary training other than higher education are also subsidized to some degree, for instance through free tuition in vocational schools. Hence, extending the current analysis to post-secondary education in general would be an interesting avenue for future research.

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Appendix

Table A1: OLS wage regressions

	Women, academic	Men, academic
Experience/10	0.481***	0.455***
	(0.106)	(0.110)
Experience^2/100	-0.198*	-0.0862
	(0.106)	(0.0981)
Experience^3/1,000	0.0381	0.00472
	(0.0398)	(0.0330)
Experience^4/100,000	-0.0252	-0.000919
	(0.0491)	(0.0369)
Tenure/10	0.494***	0.302***
	(0.0681)	(0.0601)
Tenure^2/100	-0.305***	-0.172***
	(0.0783)	(0.0663)
Tenure^3/1,000	0.104***	0.0463*
	(0.0323)	(0.0261)
Tenure^4/100,000	-0.126***	-0.0445
	(0.0424)	(0.0330)
Age/10	4.743***	5.154***
	(1.421)	(1.655)
Age^2/100	-1.522***	-1.474**
	(0.515)	(0.577)
Age^3/1,000	0.211***	0.177**
	(0.0808)	(0.0872)
Age^4/100,000	-0.110**	-0.0769
	(0.0464)	(0.0482)
Humanities	0.0230	0.0765*
	(0.0363)	(0.0428)
Social Sciences	0.0693**	0.179***
	(0.0305)	(0.0330)
Math/Natural Sciences	0.152***	0.258***
	(0.0377)	(0.0355)
Medicine	0.358***	0.416***
	(0.0402)	(0.0415)
Engineering	0.0380	0.215***
	(0.0414)	(0.0327)
Only bachelor degree	-0.158***	-0.135***
	(0.0174)	(0.0162)
Migration background	0.0104	-0.0438**
	(0.0235)	(0.0201)
Constant	-3.067**	-4.193**
	(1.457)	(1.742)
Orthog. state dummies	yes	yes
Year dummies	yes	yes
N	15701	19639

Notes: This table presents the coefficients of OLS wage regressions separately for men and women with higher education degrees. Dependent variable is the log gross hourly wage. The base category for the fields of study is is the residual category “other”. Standard errors clustered on the individual level shown in parentheses. * / ** / ***: statistically significantly different from zero at the 10%- / 5%- / 1%-level. All estimations include dummies for survey year, and orthogonalized dummies for federal states.
Source: Own calculations based on SOEP v35, waves 1985–2018.

Table A2: Conditional Logit estimates

Lifetime income/1000	0.00105**
	(2.79)
alternative_a1	-0.655***
	(-5.02)
Parents: Low education_a1	-0.811***
	(-5.60)
Parents: Medium education_a1	-0.665***
	(4.25)
Migration _Background_a1	0.902***
	(4.15)
Parents: Low occupation_a1	-0.0921
	(-0.46)
Parents: Medium occupation_a1	-0.381***
	(-2.95)
Cognitive_skills_1_a1	1.005 ***
	(13.33)
Female_a1	-1.076***
	(-8.46)
alternative_a2	-1.394***
	(-9.38)
Parents: Low education_a2	-1.087***
	(-7.53)
Parents: Medium education_a2	-0.405**
	(-2.77)
Migration _Background_a2	0.190
	(0.78)
Parents: Low occupation_a2	-0.177
	(-0.87)
Parents: Medium occupation_a2	0.105
	(0.85)
Cognitive_skills_1_a2	-0.561***
	(7.63)
Female_a2	1.027***
	(7.48)
alternative_a3	-0.866***
	(-6.60)
Parents: Low education_a3	-0.989***
	(-6.99)
Parents: Medium education_a3	-0.557***
	(-3.81)
Migration _Background_a3	1.020***
	(4.89)
Parents: Low occupation_a3	-0.164
	(-0.81)
Parents: Medium occupation_a3	-0.257*
	(-2.08)
Cognitive_skills_1_a3	1.109***
	(15.16)
Female_a3	-0.587***
	(-4.91)
alternative_a4	-3.138***
	(-11.76)
Parents: Low education_a4	-1.469***
	(-5.59)
Parents: Medium education_a4	-0.776***
	(-3.14)
Migration _Background_a4	1.414***
	(4.03)

Parents: Low occupation_a4	-0.737
	(-1.66)
Parents: Medium occupation_a4	-0.276
	(-1.30)
Cognitive_skills_1_a4	1.235***
	(9.76)
Female_a4	0.856***
	(3.95)
alternative_a5	-2.194***
	(-9.63)
Parents: Low education_a5	-0.916***
	(-3.95)
Parents: Medium education_a5	-0.568*
	(-2.33)
Migration _Background_a5	0.428
	(1.08)
Parents: Low occupation_a5	-0.635
	(-1.68)
Parents: Medium occupation_a5	-0.311
	(-1.53)
Cognitive_skills_1_a5	0.592***
	(4.91)
Female_a5	0.495*
	(2.37)
alternative_a6	-0.256*
	(-2.32)
Parents: Low education_a6	-0.925***
	(-7.76)
Parents: Medium education_a6	-0.406**
	(-3.26)
Migration _Background_a6	0.482*
	(2.55)
Parents: Low occupation_a6	-0.429*
	(-2.51)
Parents: Medium occupation_a6	0.286**
	(-2.77)
Cognitive_skills_1_a6	0.602***
	(9.86)
Female_a6	0.110
	(1.04)
N	26741

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] The table displays the coefficients estimates of the Conditional Logit model. “alternative_a1”-“alternative_a6” indicate alternative-specific dummy variables and suffixes like “_a1” to “_a6” indicate interactions with characteristics such as parental education or cognitive skills with the alternative-specific dummies. The alternatives are numbered as their alphabetic ordering: (1) Engineering, (2) Humanities (3) Math/Natural Sciences (4) Medicine (5) Other (6) Social Sciences, and vocational training is the base category.
[b] Source: SOEP, NEPS, own calculations.

Table A3: Predicted elasticities for each field

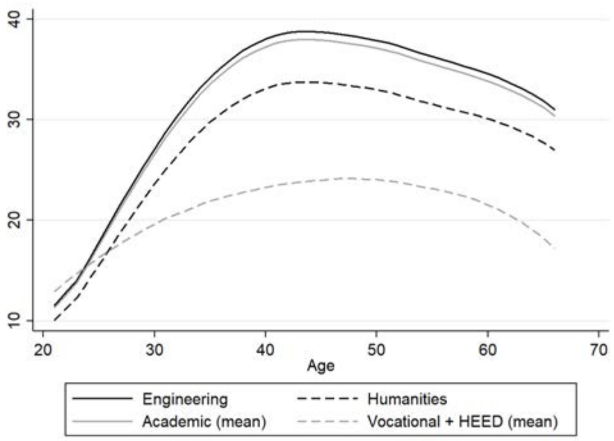
Field	Change in probability in % if net lifetime income increases by 10%
Engineering	6.51
Humanities	6.19
Math and Natural sciences	6.82
Medicine	8.68
Social sciences	5.34
Other	6.73
Vocational	4.48

Notes: The table lists the average relative changes in probabilities for a 10% increase in net lifetime income for each field (including vocational training). The quantities presented are equal to 10 times the elasticity.

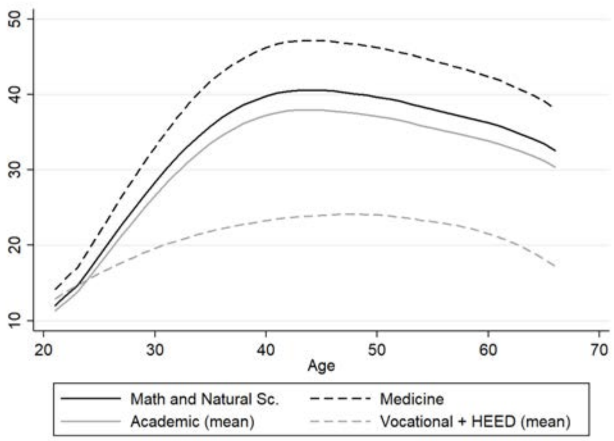
Sources: NEPS, own calculations.

Figure A1: Simulated hourly wage profiles by field of study, men

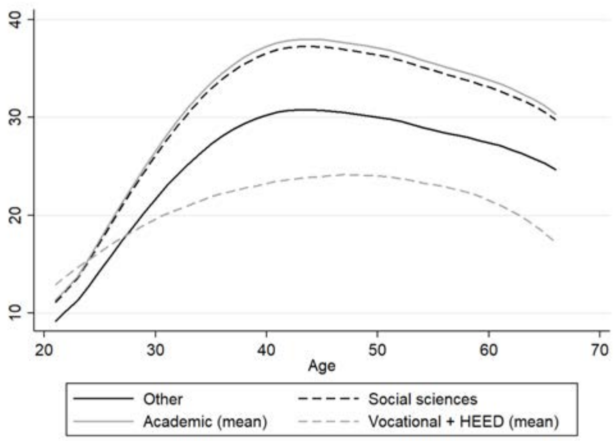
(a) Engineering, Humanities



(b) Math and Natural Sciences, Medicine



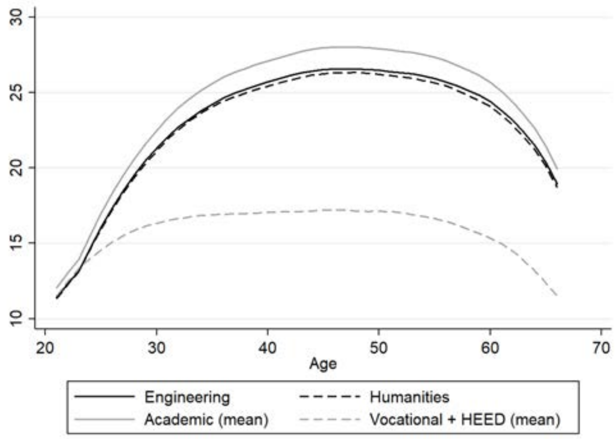
(c) Social sciences, Other fields



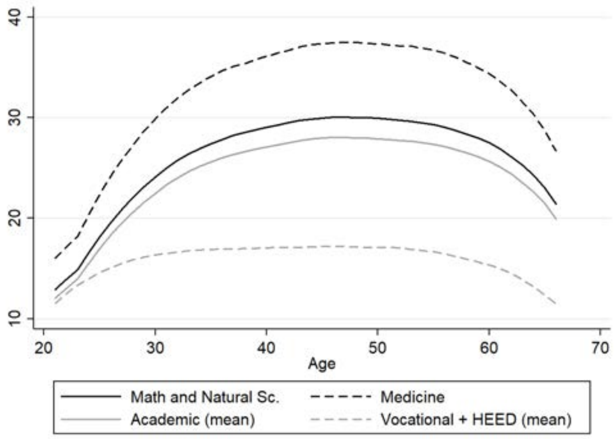
Notes: The figure depicts simulated gross hourly wages by field of study for men in Euros. Panel (a) is for the fields engineering and humanities, panel (b) is for math and natural sciences and for medicine, and panel (c) is for social sciences and other fields.
Source: Own simulations.

Figure A2: Simulated hourly wage profiles by field of study, women

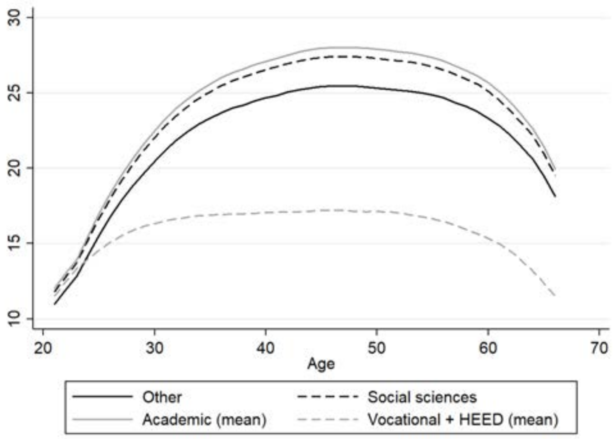
(a) Engineering, Humanities



(b) Math and Natural Sciences, Medicine



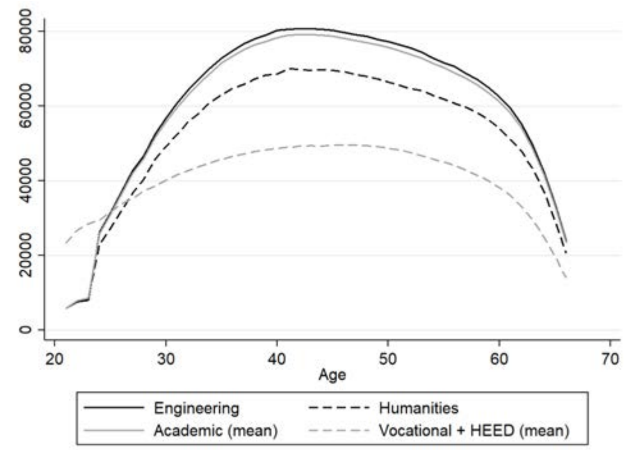
(c) Social sciences, Other fields



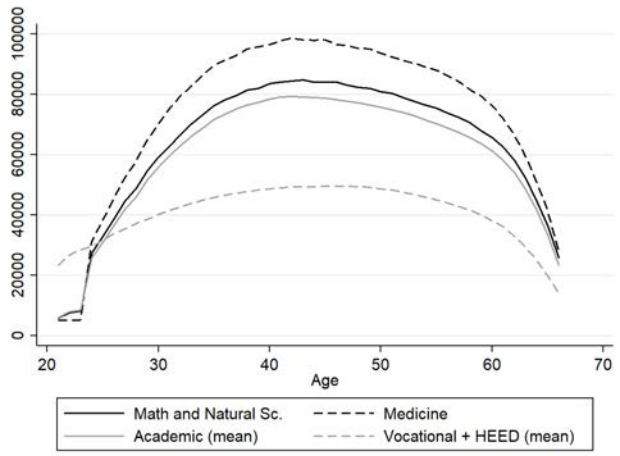
Notes: The figure depicts simulated gross hourly wages by field of study for women in Euros. Panel (a) is for the fields engineering and humanities, panel (b) is for math and natural sciences and for medicine, and panel (c) is for social sciences and other fields.
Source: Own simulations.

Figure A3: Simulated annual labor earnings profiles by field of study, men

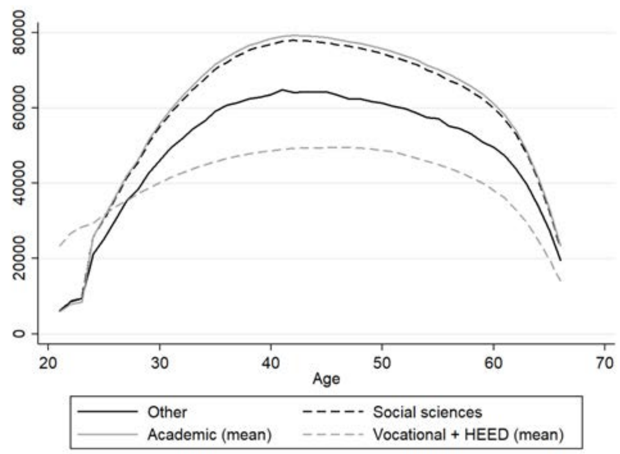
(a) Engineering, Humanities



(b) Math and Natural Sciences, Medicine



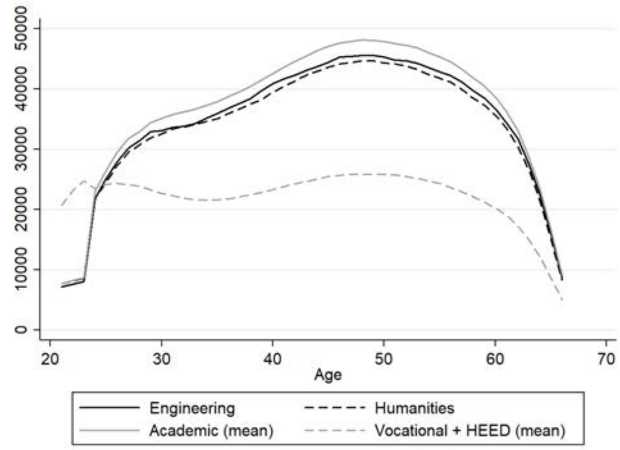
(c) Social sciences, Other fields



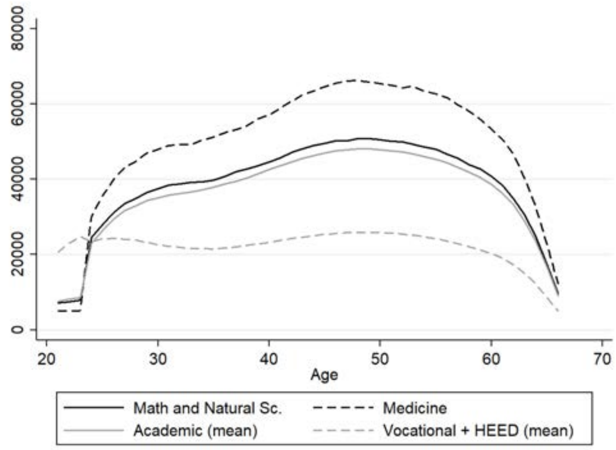
Notes: The figure depicts simulated annual labor earnings by field of study for men in Euros. Panel (a) is for the fields engineering and humanities, panel (b) is for math and natural sciences and for medicine, and panel (c) is for social sciences and other fields.
Source: Own simulations.

Figure A4: Simulated annual labor earnings profiles by field of study, women

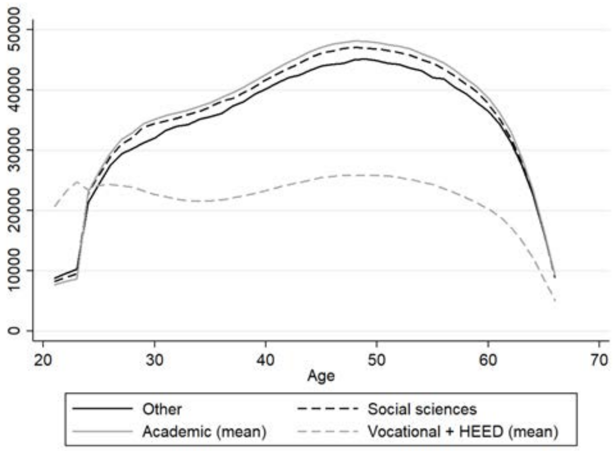
(a) Engineering, Humanities



(b) Math and Natural Sciences, Medicine



(c) Social sciences, Other fields



Notes: The figure depicts simulated annual labor earnings by field of study for women in Euros. Panel (a) is for the fields engineering and humanities, panel (b) is for math and natural sciences and for medicine, and panel (c) is for social sciences and other fields.
Source: Own simulations.

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