



The Effects of Student Aid - Evidence from Germany

Master's Thesis
in Economics (Science Track)

by

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Abstract

This thesis uses German panel data (SOEP; 2002–2019) to investigate the effect of BAfoeG, an example for a means-tested student aid within a corporatist welfare state, on *Enrollment*, *Labor Supply*, and *Non-Take-Up* decisions.

Using a fixed-effects model, the calculated mechanical BAfoeG variation, BAfoeG max. rate and the variation in time of the real value, a positive effect of 1.1–1.3 pp on enrollment is indicated for a 10 % increase in the real max. rate. The enrollment reaction seems to be more elastic for younger individuals. However, a null-effect of individual changes rather than the max rate can not be falsified. Further, the effect of max. rate seems to rather affect estimated non-recipients than recipients, which could be driven by a misperception of BAfoeG as well as a negative externality of increasing market tightness. These results, which are rather correlational than causal, are not very robust, e.g. for changes in the time period.

In an IV setup with the mechanical BAfoeG variation as instrument for the simulated BAfoeG it is shown that the inverse relationship of potential BAfoeG and non-take-up is not as pronounced as anticipated (-0.0001 pp for 100€ increase in simulated BAfoeG). This suggests that either misperception about the BAfoeG reception exists over the full income distribution or, more general, that the low BAfoeG recipients are not the driving force, as it was anticipated before.

Using a similar setup for labor supply, it is also visible that the negative incentive effects of more student aid both on the extensive margin and intensive margin are much smaller than in pooled regression which still includes the endogeneity issue. Hence, if one assumes this difference is purely driven by simultaneity, one could argue for a relaxation of BAfoeG's own income constraint.

DISCLAIMER: *AI (ChatGPT & DeepL) was only used in the following ways: (1) to identify grammatical and typographical errors (ex-post; chapter wise, AI identifies weaknesses & I manually correct), and (2) to suggest synonyms for in my view not-fitting words or phrases (while writing; only sentence fragments chosen by myself).*

Acknowledgement

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1 Introduction

Increasing skill premia, demographic challenges and positive productivity effects – expenditures on education remain as critical drivers from the states' points of view to address not only today's but also tomorrow's challenges. This also holds for tertiary education and state-funded student aid, with a high number of students relying on financial support from the state. Yet, the design of student aid varies a lot between different welfare states, and empirical evaluations remain rare, leaving the distinct effects as well as mechanisms of student aid policies to some extent unquantified.

How does means-tested student aid affect (i) the decision to enroll, (ii) the decision to take up student aid, and (iii) labor supply during studies? Generally, means-testing relies on screening to target financial aid towards those who meet specific eligibility criteria, ensuring that resources are allocated to those in need. However, it also depends on opt-in principles and deductions, raising questions about potential negative incentive effects. With respect to means-tested student aid, particularly Germany's BAföG, similar considerations arise. One would expect that – given a nuanced screening – the student start decision displays a high elasticity related to the student aid. On the other hand, more financial means due to higher student aid could lead to less incentive to supply labor during the studies. Further, are there reasons to not take up student aid, e.g. socio-economic induced barriers?

Focusing on a few precise mechanisms of student aid and one policy instrument, namely the financial amount of student aid, is hereby in line with the literature. As stated by [Joensen and Mattana \(2024\)](#), complex eligibility, the variety of programs and the unobserved counterfactual otherwise make it hard to causally identify any effects (see [Deming and Dynarski, 2010](#) for further challenges). The variety of programs is implicitly stemming from the variety in welfare state types explained by [Esping-Andersen \(1990\)](#), with means-tested student aid resembling the corporatist, central European welfare state. Consequently, it must be distinguished from the Nordic welfare state, which adopts a more universal approach by viewing educational spending as an active form of redistribution ([Andersen, 2008, 2018](#)). Similarly, it differs from the Anglo-Saxon welfare state model, in which student funding relies more heavily on individual debt but, as a consequence, has lower income taxes (as seen implicitly in [Black et al., 2023](#); [Joensen and Mattana, 2024](#); [Lochner and Monge-Naranjo, 2012](#)). Thus, it has to be differentiated between the broad and the precise level of literature.

On the broad level of literature, short term effects can be shown on four areas, "college enrollment, persistence, performance, and graduation" ([Joensen and Mattana, 2024](#), p.5). A positive effect on college enrollment is visible in both the Nordic ([Nielsen et al., 2010](#)) and the Anglo-Saxon welfare states ([Deming and Dynarski, 2009](#)), with the latter effect being larger (1.35 percentage points vs. 2-5 percentage points for a 1000 \$ increase; see [Mattana, 2018](#) for a review and discussion). Further, it has been shown that dropouts seem to decrease with increasing student aid (Anglo-Saxon: see [Bettinger et al., 2004](#) or [Dynarski, 2003](#); Nordics: see [Arendt, 2013](#)) and students seem to live in better neighborhoods ex-post ([Bettinger et al., 2019](#); [Scott-Clayton and Zafar, 2016](#)). Yet, one has to be aware that most of these studies rely on specific reform changes suitable for a regression discontinuity design, such as the 1988 reform in Denmark. While this approach provides a strong basis for causal identification, it also raises concerns about the validity of these effects in today's environment.

Looking precisely at Germany, however, the picture is not as clear. On the one hand, no such (quasi-)experimental setup is possible, leading to mixed results. [Baumgartner and Steiner \(2005\)](#) is the only paper attempting a quasi-experimental approach for the 1990 reform, which could be interpreted as showing a non-effect (as e.g. [Mattana, 2018](#) interprets it). However, it rather reflects the effect of a shift in the grant-loan ratio without direct (short-term) consequences on the students' budget constraint. In contrast, [Lauer \(2002\)](#) find a positive effect (0.8 percentage points for 1000 DM, which is about 500 €). Nonetheless, as correctly stated by [Baumgartner and Steiner \(2005\)](#), the discrete choice model might be biased due to endogeneity caused by the inclusion of BAfoeG indicator variables. Yet, the only existing literature that attempts to validly overcome the endogeneity problem is the microsimulation literature, which simulates counterfactual BAfoeG values. Notable studies include [Herber and Kalinowski \(2019\)](#) and [Steiner and Wrohlich \(2012\)](#), with the latter finding positive effects on enrollment of similar magnitude than [Nielsen et al. \(2010\)](#) in Denmark. [Herber and Kalinowski \(2019\)](#) analyze the issue of non-take-up due to the opt-in design and identify potential reasons.

Another issue in Germany is the high complexity of BAfoeG itself. The calculation of BAfoeG is governed by the respective law, the Bundesausbildungsförderungsgesetz (BAföG¹), and involves the following calculation algorithm, which is presented in a very simplified form². Firstly, the student's own net income and assets are assessed, followed by the income of their spouse or parents, if applicable (see §§ 21-24 BAföG). The total amount of support is determined by subtracting these contributions from the BAfoeG max. rate (see § 13 BAföG), which varies depending on the type of educational institution and the student's living situation. Additionally, §§ 12 and 14 BAföG outline allowances and deductions for necessary expenses, e.g. health-insurance. In theory, 50 % of the student aid is a grant and 50 % a loan. However, specific allowances are a 100 % grant and the repayment is capped to 10,000 €. Hence, the loan- & grant share can differ.

The value added of this thesis is the contribution to the aforementioned microsimulation literature by simulating counterfactual BAfoeG based on the full calculation algorithm rather than an approximation, as e.g. done by [Baumgartner and Steiner \(2005\)](#). Utilizing the latest version of the SOEP, it is possible to include more years (2002–2019) while also employing a very inclusive data handling approach similar to [Glocker \(2011\)](#). Given the complexity of BAfoeG, which acts as a gate-keeper for this kind of literature, newer papers like [Fidan and Manger \(2022\)](#) still relied on the data prepared by [Herber and Kalinowski \(2019\)](#). Furthermore, this thesis will use the simulated BAfoeG, i.e., based on observables, as well as the calculated mechanical BAfoeG variation, inspired by the labor-supply literature ([Kleven and Schultz, 2014](#)), which excludes changes due to the endogenous choice of labor supply.

The thesis is structured as follows: First, [Data and Descriptive Statistics](#) are presented, focusing on the SOEP specific data handling. Second, the [Empirical Framework](#) is introduced. Following this, the [Results](#) are presented, leading into the [Discussion and Limitations](#). The latter addresses potential treatment heterogeneity and includes robustness checks. Finally, the thesis concludes with a [Summary and Concluding Remarks](#).

¹In this thesis: "BAföG" refers to the law as source, while "BAfoeG" refers to the student aid.

²There are very specific rules, such as how distinct income types are considered or standard deductions for social contributions. These rules are clearly outlined in the respective sections of the BAföG law and, although not covered in this description for the sake of simplicity, they are included in the calculations. The most important aspect to understand is that any own income above the threshold is fully deducted (negative incentive effect), while for parental (in period t-2) or spouse income above the threshold, only a share is deducted from the individual's max. rate (no incentive for behavioral changes).

2 Data and Descriptive Statistics

In order to identify the effect of Germany's state funded student aid, BAfoeG, this thesis relies primarily on the German Socio Economic Panel (SOEP, 2023) enhanced by inflation- (Destatis, 2024b) as well as average wage- data (Destatis, 2024a) by the Federal Statistical Office of Germany. The SOEP is a longitudinal survey beginning with 1984, which involves nearly 15,000 households and around 30,000 individuals (Goebel et al., 2019). As explained in Goebel et al. (2019), random probability samples are used, with general population samples being drawn through a nationwide two-stage stratified sampling procedure and panel attrition being addressed by the incorporation of refreshment samples. Thus, it can be considered representative w.r.t. Germany.

The main contribution of this thesis is the micro-simulation of the student aid (BAfoeG) received to address the underlying edogeneity issue of observational data allowing a shot for a causal identification (similar to Herber and Kalinowski, 2019). Based on the underlying SOEP variables, it is possible to estimate a *Simulated BAfoeG*, i.e., BAfoeG determined by observable characteristics if an individual were to apply for it. Furthermore, it is possible to estimate a *Mechanical BAfoeG*, i.e., BAfoeG if an individual were to apply for it without deducting their own income. While this distinction may seem trivial, Figure 1 shows the differences over time. It is visible that, on average, more than 20 % of students actually receive BAfoeG (black line). However, the Simulated BAfoeG (orange line) shows that, on average, more than 30 % could receive BAfoeG if they were to apply. Hence, the difference between the two lines is purely *Non-Take-Up*. The Mechanical BAfoeG (blue line) shows that, on average, more than 40 % could receive BAfoeG if they did not work. Hence, the difference between these lines highlights the unconsidered endogeneity in basic correlational studies that use only the observed amount of BAfoeG one is receiving (see Figure 13 in Appendix for visualization of decision nodes).

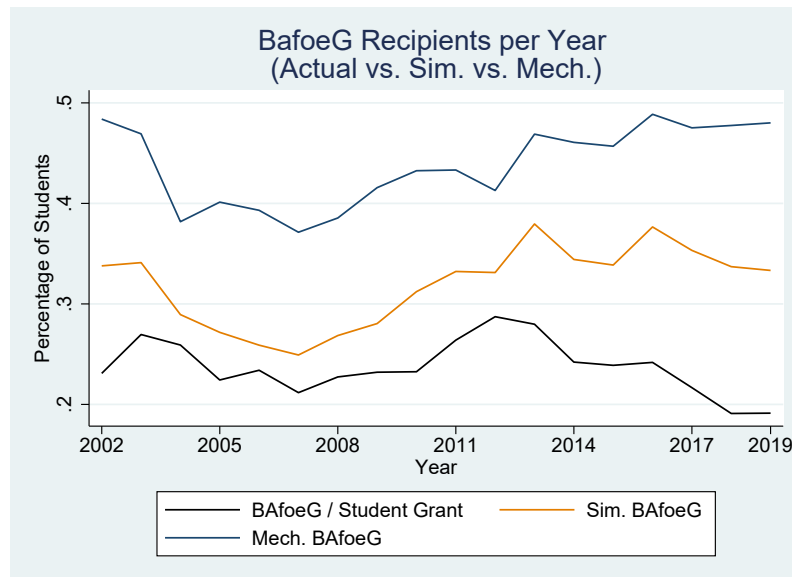


Figure 1: BAfoeG Recipients per Year; Actual vs. Simulated vs. Mechanical BAfoeG

Yet, this calculation is based on the specific data handling of the SOEP and differs from that of Herber and Kalinowski (2019). While Herber and Kalinowski (2019) adopted a very restrictive approach regarding the student sample, this thesis includes as many student observations as possible through imputations and an inclusive student

definition (similar to the definition in [Glocker, 2011](#)).³ The aim of this inclusive approach is to maintain the representativeness of the SOEP dataset, as restrictive criteria could selectively exclude non-traditional educational paths. Even though, the overview provided by [Table 9](#) (Appendix) covers the creation of the core variables needed to replicate this thesis, it is necessary to discuss data decisions with potential identification impact.

Arguably, the most influential data decision in this thesis is to drop individuals who lack any information about their parents as this is needed for the BAfoeG calculation. Specifically, individuals are retained as long as there is information on at least one parent. A prominent example is only the mother is included and the father's information is missing (Father's SOEP ID missing and not answered the question w.r.t. status of his/her father). In those cases, the father is treated as dead w.r.t. BAfoeG calculations but the individual is kept. Additionally, individuals are kept if both parents are dead but the IDs are missing in the SOEP. While this decision could introduce a bias, the descriptive statistics (see [Figure 15](#), Appendix shows no indication of such). There exists a minor difference in income and BAfoeG, which is within the range of one standard deviation. This difference is mostly driven by the age difference, since the likelihood of the parents not being in the SOEP increases by design in age. Thus, the considered students should tilt more towards, what in public debates is considered "true students".

The definition of a student follows [Glocker \(2011\)](#). A person is considered a student if they are enrolled for at least one month of the semester at a German University. Technically, this means that the binary-string education variable (pab0013) is decoded to form the basis of the student identifier. Subsequently, this identifier is corrected based on eligibility to study, age, and university type. It is reasonable to assume that students' weekly working hours are capped at 80, making it impossible to work more than 40 hours alongside full-time studies. Therefore, students reporting working hours beyond this limit are disregarded. Additionally, the top 5 % of income earners are excluded to account for full-time workers who are merely enrolled in studies. As [Table 1](#) shows, still some high earning students are included, which, however, seems reasonable.

For BAfoeG, the parental and spouse income from two years before studying is relevant, whereas for the student's own income, the current year's income is considered. Technically, this means the sum of all positive income (§ 2 EStG). Therefore, all income streams are considered, as listed in [Table 9](#) (Appendix). If the parental main income is missing in the specific wave, it is either imputed if possible.⁴ Otherwise, the income from one year prior or the current income is in this order taken. Income is therefore income in the sense of BAfoeG (see §21 IV BAföG) and excludes: BAfoeG itself, alimony, unemployment benefit II, housing benefits, parental allowances, maternity benefits, social assistance and loans.

³Restricting the data sample based on the approach by [Herber and Kalinowski \(2019\)](#) yields similar student and BAfoeG recipient numbers, which validates the BAfoeG calculation and general data cleaning. This verification was conducted as part of the Fraunhofer FIT project work to verify my model and not by myself.

⁴The labor supply and wage are imputed using a Heckman correction, which was already integrated into a Fraunhofer FIT labor supply model. It estimates four different equations (male/female, west/east) and includes the following variables: age, age², educational levels, time since apprenticeship, time since apprenticeship² divided by 100, years of unemployment or out of the labor force, labor market experience full time, labor market experience full time² divided by 100, labor market experience part time, labor market experience part time² divided by 100, degree of disability, degree of disability² divided by 100, children under 3 years old, children under 6 years old, children under 16 years old, state in Germany, and the tax scheme in the respective year. Strong outliers in hourly wages are removed by excluding the upper and lower 2 % from the estimation.

Based on this BAfoeG relevant gross income, a standard social deduction is calculated (percentage based on work type according to § 21 II BAföG 1–4). Further, based on the so-called "Programmablaufplan" (BMF, 2024), it is possible to manually estimate income tax, church tax, and the solidarity surcharge (Soli). Thus, the gross income minus the standard social deduction and taxes results in the BAfoeG relevant net income.

However, it is important to note that this calculation does not account for income outside of Germany if it is not included in the SOEP reportings (see § 21 Abs. 2a BAföG) and is conditional on the optimal behavior assumption. It is required to assume that individuals behave optimal w.r.t. their taxation. An example is the choice of tax class in marriage. In case of missing tax classes, it must be assumed that households minimize the taxes during the year. However, as Buettner et al. (2019) show, in practice this might not always hold true. Additionally, specific tax breaks that can be interchanged between years (e.g. "Verlustvortrag") can not be considered. The same applies to income that is tax-free under the so-called Trainer's Allowance or Volunteer Allowance. Furthermore, the SOEP does not adequately capture wealth, and hence, it is not considered in the calculation.⁵ Additionally, the specific handling of the "Riester-Rente" is also not accounted for.

After the data cleaning, the dataset contains 12,589 student observations from 3,824 distinct students (see Table 1). While Herber and Kalinowski (2019), using a restrictive data approach, report 986 student observations classified as non-take-up or take-up (2002-2013), this thesis identifies 133 % more students in the same subsample, totaling 2,327. However, the main characteristics are roughly the same. While some differences between Table 1 and Herber and Kalinowski (2019) can be attributed to time trends (e.g., the share of males or migration background), the differences in household with parents and labor supply (hrs.) arise from the distinct data decisions. As the SOEP variable for household does by design not purely reflect the actual living place for a student, it is corrected as accurately as possible (e.g. by the question where the parents live). Consequently, this thesis reports a share of roughly 43 % of students living at home, which aligns more closely with the roughly 20-30 % reported in questionnaires such as Seegers et al. (2023). While most of the differences in labor hours can be attributed to variations in reporting (with averages taken over all student observations), a small difference remains. This is driven by their strict exclusion criteria, which exclude more non-traditional career paths.

The in the sample reported BAfoeG numbers of approx 24 % are slightly higher than official reporting Federal Government of Germany (2023). Main reasons is that the SOEP in some waves the question included merit-based students grants. However, share of merit-based study grants remains rather constant (SEE SOURCES) s.t. bias also should be constant. This is also visible that decline in share is equally visible in official reporting and in this thesis (see Table 8, Appendix). Furthermore, students above the age of 35 and some students who are fully in the labor force are excluded. Thus, the slightly higher share is in line with official reports. Additionally, the approximate 32 % share in sim. BAfoeG aligns with the only similar estimation by Herber and Kalinowski (2019). However, one must be aware that it is not possible to exclude students based on wealth and the regular student time per degree⁶ based on the SOEP. Hence, simulations are potentially overestimated and rely on the assumption that this bias remains constant.

⁵Although, in theory, one could try to estimate wealth through rental and capital income, this approach is problematic. In practice, it results in an unreasonably high number of BAfoeG recipients being simulated with no BAfoeG, as these forms of income correlate not only with the amount of wealth but also with its forms, risk preferences, and the potential for intertemporal shifting.

⁶It is only possible to correct for clear cases that exceed the regular time for all possible degrees.

Table 1: Summary Statistics Students (2002-2019)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
<i>Individual Characteristics:</i>					
Age	12589	23.5436	3.2963	17	35
Male	12589	.4799	.4996	0	1
HH with Parents	12589	.4273	.4947	0	1
Migration Background	12589	.2273	.4191	0	1
First Gen	12589	.3395	.4736	0	1
<i>Academic:</i>					
University	12589	.7283	.4448	0	1
Polytechnic	12589	.2332	.4229	0	1
Work Academy	12589	.0274	.1633	0	1
Year in University	12589	3.3196	2.3323	1	16
<i>Income:</i>					
Inc. Student (€, Gross, Mth.)	12589	506.285	690.0756	0	3000
Labor Supply	12589	.4902	.4999	0	1
Labor Supply (Weekly Hours)	6171	20.3635	12.6687	1	40
Inc. Father (€, Gross, Mth.)	12589	4068.4187	5151.7772	0	92318
Inc. Mother (€, Gross, Mth.)	12589	1785.1596	2277.5304	0	72000
<i>BAfoeG:</i>					
Student Grants (SOEP)	12589	.2361	.4247	0	1
Student Grants (€, Mth.)	2151	430.0014	236.917	10	3000
BAfoeG (Simulated)	12589	.3220	.4673	0	1
BAfoeG (Simulated, €, Mth.)	4054	358.6306	206.7908	10	2599
BAfoeG (Mechanical)	12589	.4418	.4966	0	1
BAfoeG (Mechanical, €, Mth.)	5562	388.0062	210.0179	10	2599
Eligible for BAfoeG	12589	.8989	.3015	0	1

Note: This includes every individual who studied for at least one semester in the respective year. Consequently, individuals appearing in j study years influence the mean with a weighting of j/n . Student Grants include state funding (BAfoeG) as well as other forms of stipends. BAfoeG amounts are calculated under the assumption of optimal behavior and always assume an application is made if the amount is greater than zero. Therefore, these figures may be higher than the actual amounts received.

To access the quality of simulation and the non-take-up-rates, this thesis follows [Herber and Kalinowski \(2019\)](#), who themselves follow [Bargain et al. \(2012\)](#). The non-take-up rate (NTU) can be expressed as share of simulated eligible (SE) and reported recipients (BAF),

$$NTU = \frac{SE - (BAF|SE)}{SE} = \frac{\overline{BAF}|SE}{SE}. \quad (1)$$

The quality of the simulation can – to some extent – be evaluated over the beta error rate,

$$\beta = \frac{BAF|\overline{SE}}{BAF}, \quad (2)$$

which captures the share of falsely simulated students. Yet, as briefly mentioned by

Herber and Kalinowski (2019), a low but non-zero beta error rate does not imply that the simulation is incorrect. Rather, it reflects the complexity of means-testing combined with the absence of specific variables (e.g. subject data) and potential measurement errors (e.g. false reportings). Consequently, as also done by the respective literature, the lower bound non-take-up rate (NTU_{LB}) can be expressed as

$$NTU_{LB} = \frac{\overline{(BAF|SE)}}{SE + (BAF|\overline{SE})}, \quad (3)$$

while the NTU itself can be considered the upper bound.

Given the data decision and the extended sample, the beta error rate is with approx 20 % significantly higher than the approx 8 % in Herber and Kalinowski (2019), which is the main disadvantage of the inclusive student definition and imputations. However, Herber and Kalinowski (2019) additionally decided to be less restrictive in their BAfoeG calculations, for close deviations as they started with β of approx. 16 %, which is in line with this thesis' results (see their Table 11, p. 57).

Yet, as visible in Figure 2, the non-take-up rate itself (black lines) ranges from roughly 40–55 % in 2004 to 55–65 % in 2018. While such high numbers may initially seem incorrect, they are only slightly higher than general estimates for social assistance non-take-up in Germany, which range from 34–43 % (Bruckmeier et al., 2013), with the main differences occurring from 2015 onward. Furthermore, it is visible from the simulated mechanical BAfoeG (yellow) the potential dark number of non-take-up cases, which had not been covered in literature before, peaking at roughly 65–75 % in 2018. This group includes students who potentially work and, thus, do not take up BAfoeG (by choice) because it would potentially not be sufficient. It is further visible in Figure 3 that these differences are consistent for the first and second parental income quartiles, with the non-take-up rate being slightly higher for the second income quartile. This could indicate that they either do not know about BAfoeG or do not need it. The significant differences in the third quartile primarily stem from the small sample size in this group, combined with the fact that it is very rare to receive BAfoeG in this income range (only in very specific cases, such as families with many children or siblings).

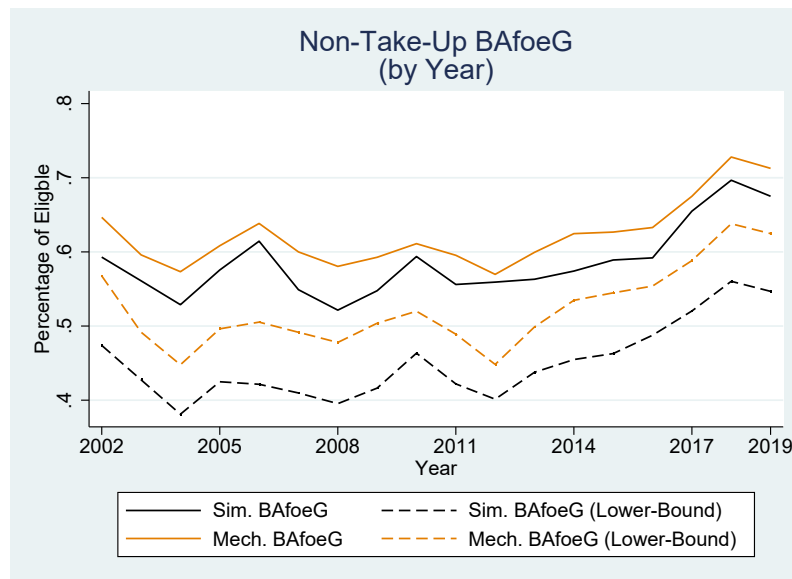


Figure 2: Non-Take-Up by Year (Upper vs. Lower Bound & Sim. vs. Mech. BAfoeG)

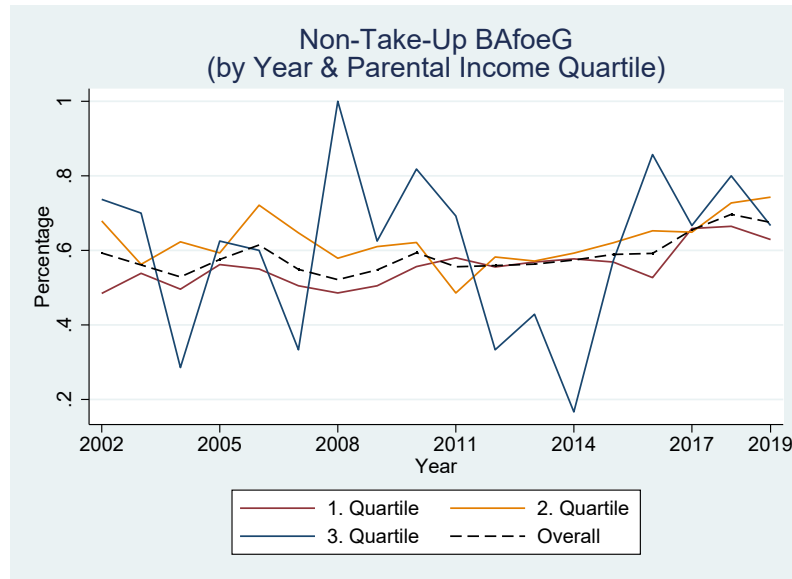


Figure 3: Non-Take-Up by Year & Parental Income Quartile (Upper Bound)

The sub-sample considered for the enrollment decision includes all individuals under 35 years old who have the respective qualifying high school degree, are not students, and do not have any degree ($n = 25,458$; see summary Table 10, Appendix), together with the first-year student observations ($n = 3,353$). Consequently, the decision to enroll only captures the first tertiary degree (usually Bachelor). This sub-sample now considers 9,081 different individuals and e.g. indicates parental income differences between students and non-students. However, as visible in Figure 4, the summary statistics Table 10 (Appendix) are skewed to the right since students who start studying tend to start relatively earlier (approximately 20+ % for age < 22) and, hence, leave the panel. Nonetheless, small differences between subgroups like first-generation students exist (also visible in Figure 14, showing the variation over time).

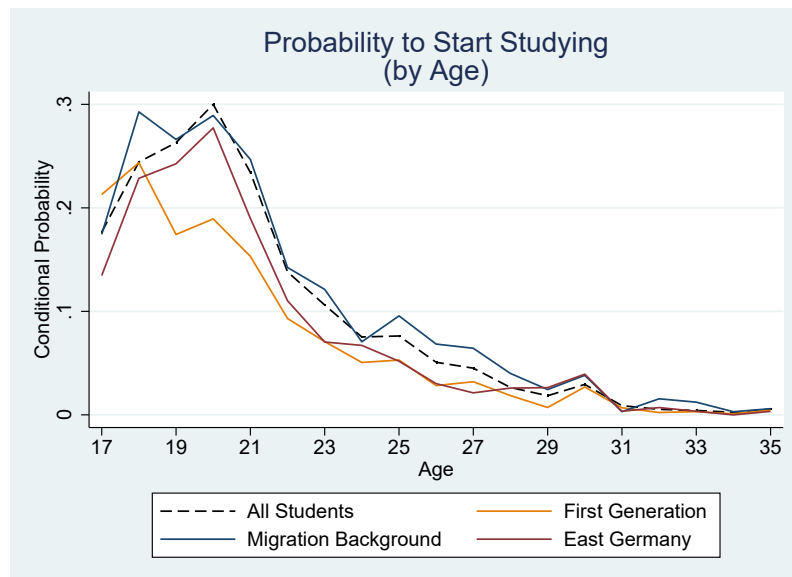


Figure 4: Probability to Enroll by Age & Subgroup

3 Empirical Framework

The main empirical setting used in this thesis is the variation in real BAfoeG over time. As shown in Figure 5, Germany experienced several changes in the nominal value of BAfoeG from 2002 to 2019 (see the change of further parameters in Figure 9 ff., Appendix). As a consequence, this leads due to changing price levels to constant variation in real BAfoeG. This setting, by design, assumes that inflation is orthogonal to students' behavior. Given that only pre-COVID data is included and inflation (mostly) follows the same gradient in this period, this assumption appears reasonable.

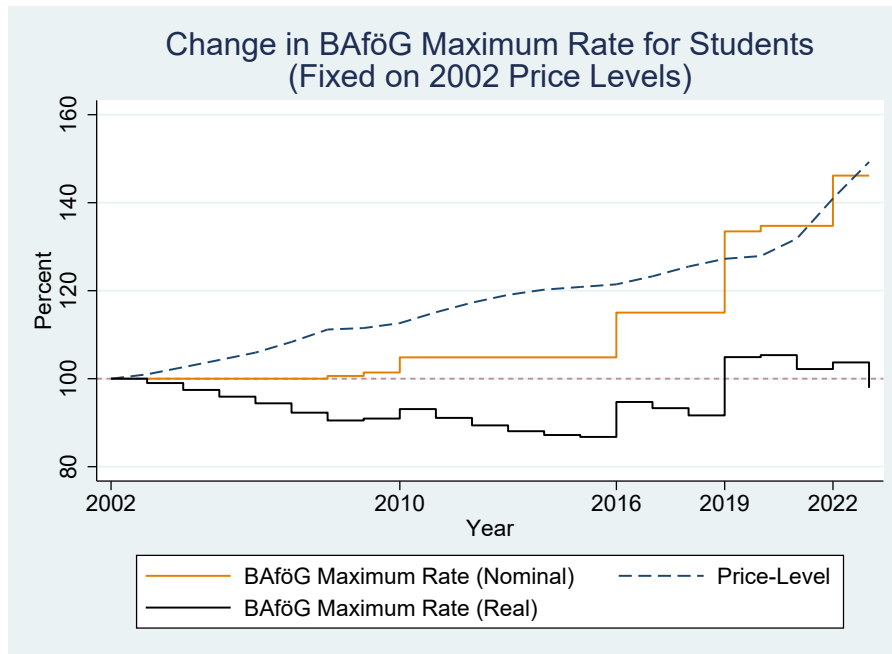


Figure 5: Change of BAfoeG Maximum Rate in Time

As introduced before, there exist two streams of exogenous variation for real BAfoeG values. While Figure 5 captures the real variation in the max. rate, it should be noted that the absolute value differs depending on the living situation, with students living at home having a smaller max rate.⁷ Changes in the max. rate impact mechanical, simulated, and actual BAfoeG values by altering the base amount before deductions. Two effects are possible: first, a full pass-through effect when BAfoeG remains significantly above zero, and second, a negligible effect when BAfoeG drops to zero post-deductions for the specific student. Thus, Mechanical BAfoeG captures more variation, as it includes the changes due to deductions and allowances, which otherwise is not captured. Simulated/actual BAfoeG would reflect the full variation, however, including the observed variation from the endogenous labor supply decision. Hence, it can not be used as exogenous variation.

⁷The term "maximal BAfoeG" differs slightly from its use in political discourse, where it assumes a student who does not live at home and must cover insurance costs, thus receiving additional allowances (typically applicable to students 25 years and older). Moreover, BAfoeG is not strictly capped, as flat allowances for children can increase the support available, making it technically unbounded. Therefore, "maximum rate" refers to BAfoeG before any income deductions and allowances are applied.

3.1 Enrollment (FE Estimation)

To determine the effect on enrollment, both the real variation in the maximum BAfoeG rate and the Mechanical BAfoeG are considered. The maximum rate BAfoeG is directly visible, while the Mechanical BAfoeG is now being made observable through the simulation excluding the labor supply choice. This is especially important as non-students are also within the considered subset, reporting a higher wage as a consequence of not studying.

In a standard approach, one would begin with a (naive) pooled pre-regression, estimating the conditional probability of student i enrolling at a given point t in the following form:

$$PR_{it}(\text{Enroll} \mid \text{Eligible}) = \beta_0 + \beta_1 \times \text{BAfoeG Max Rate}_t + W'\zeta + \varepsilon_{it}. \quad (4)$$

This typically includes socio-economic controls ($W'\zeta$) and β_1 is the (causal) effect of interest capturing the variation in maximum BAfoeG rate. Since it is included as a rate, it does not differ between i and only varies with t . This variation could demonstrate the perceived change in BAfoeG by students, for example, through media announcements.

Yet, this setup could still suffer from endogeneity if $W'\zeta$ does not capture all confounders. One example of a confounder, which is not directly observable and thus not implementable, is the students' general talent or preferences. In order to capture this unobserved heterogeneity a linear probability model (LPM) is estimated including individual fixed effects (μ_i),

$$PR_{it}(\text{Enroll} \mid \text{Eligible}) = \beta_0 + \beta_1 \times \text{BAfoeG Max Rate}_t + W'\zeta + \mu_i + \varepsilon_{it}. \quad (5)$$

As visible in [Table 11](#), the estimates for the marginal effect of interest do not differ between a Probit and a LPM, allowing, under a slight abuse of Kolmogorov's axioms, the use of the LPM and, thus, the inclusion of fixed effects. However, the inclusion of time fixed effects to capture general time trends is not possible as it would collide with the yearly variation.

This thesis includes a similar approach. However, through the simulated mechanical BAfoeG it is possible to extend the standard approach. By incorporating a "treatment identifier" s ,

$$PR_{ist}(\text{Enroll} \mid \text{Eligible}) = \beta_0 + \beta_1 \times \text{BAfoeG Max Rate}_{st} + W'\zeta + \mu_i + \varepsilon_{ist}, \quad (6)$$

it is possible to identify the group who might react to announced changes in BAfoeG. This identifier turns one, if the simulated mechanical BAfoeG is larger than zero, i.e. they would receive (some) BAfoeG if they do not work.

Further, in a fixed-effects model it is also possible to directly include the mechanical BAfoeG as it captures the actual differences one would encounter assuming they do not work. This can be written as

$$PR_{it}(\text{Enroll} \mid \text{Eligible}) = \beta_0 + \beta_1 \times \text{Mech. BAfoeG}_{it} + W'\zeta + \mu_i + \varepsilon_{ist}. \quad (7)$$

In all variants of the fixed effects models, it is essential to control for time-variant factors. This includes the self-reported gross income in period $t - 1$ as a proxy for the outside option, age (since it is inversely related), and living situation (living at home with parents or not).

3.2 Non-Take-Up & Labor Supply (Instrumental Setup)

In the case of non-take-up and labor supply, the primary source of endogeneity is the behavioral change due to the interlinkage between non-take-up and labor supply itself (see Figure 13, Appendix for visualization). This effect is mediated through the simultaneous causal relationship between labor supply and BAfoeG. Specifically, if a student increases their labor supply, their BAfoeG decreases. Conversely, if a student receives less aid by design, they must substitute this with more labor.

To address this issue, this thesis relies on the instrumental approach by Herber and Kalinowski (2019) used explicitly for non-take-up and uses the mechanical BAfoeG variation as the primary instrument (see Figure 6). However, there is no second instrument for "independent funding" employed, as independent funding is primarily linked to age and prior apprenticeships or jobs. Therefore, it does not provide purely exogenous variation due to its high correlation with social capital. As Herber and Kalinowski (2019) themselves state, they are the only study that uses the specific maximum rate⁸ instead of the maximum amount of benefits normally used for other social assistance programs (e.g. Bruckmeier and Wiemers, 2012). Yet, this thesis additionally includes the variation in max. BAfoeG rates instead of the mech. BAfoeG to check for potential differences.

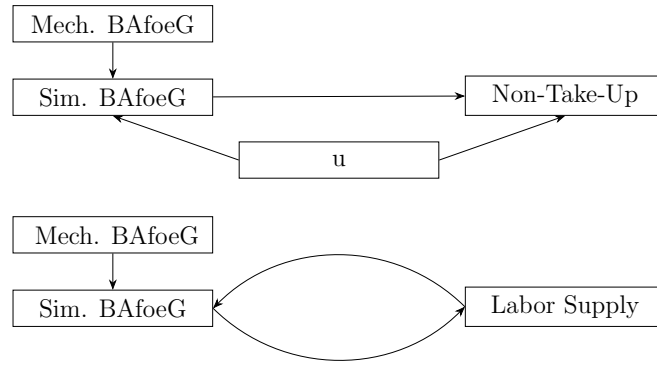


Figure 6: Instrumental Approach used for Labor Supply & Non-Take-Up

In order for mech. BAfoeG to be a valid instrument it must be relevant and exogenous. By design, mech. BAfoeG explains most of Sim. BAfoeG's variation, i.e. $Cov(\text{Mech. BAfoeG}, \text{Sim. BAfoeG}) \neq 0$ & $Cov(\text{Mech. BAfoeG}, \text{Sim. BAfoeG}) \gg 0$. Additionally, strong first stage effects are visible. Hence, mech. BAfoeG is relevant. To be exogenous, it must be orthogonal to the error term, i.e. $Cov(\text{Mech. BAfoeG}, u) = 0$. As most of the potential socio-economics factors are within the set of controls and mech. BAfoeG is constructed to contain the exogenous parts of variation, only wealth – both financially and culturally – remains as potential danger to exogeneity. While it seems unlikely that much within variation of Mech. BAfoeG can be attributed to sudden changes in (family) wealth, it is not possible to control for that due to lack of variables. Hence, it remains a risk, which should lead to different estimates when using the max. rate as a check-up. Still, mech. BAfoeG appears as exogenous, thus being a valid instrument.

⁸Herber and Kalinowski (2019) calculate individual maximum benefit amounts "by assuming that the student is not living with her [sic] parents and receives the maximum rent subsidy" (p.17) and then deduct the exogenous parts. This means what they refer to as "individual maximum benefits" is very similar to mechanical BAfoeG, except for that living assumption. In this thesis, the actual living situation is considered, with an additional control in the regressions, as otherwise potential differences between the groups might be a biasing factor.

4 Results

This section includes the presentation of the key results, divided into the subtopics [Enrollment](#), [Non-Take-Up](#) & [Labor Supply](#).

4.1 Enrollment

The main argument for an effect on enrollment is that higher financial means, in the form of BAfoeG, enable certain groups to pursue studies that would otherwise be inaccessible. For others, it increases the economic incentive to study compared to the outside option of regular employment. As shown in [Table 2](#), there is an indication of such a positive relationship between a higher BAfoeG maximum rate and the probability of enrollment.

Table 2: Enrollment: OLS/FE - Max. Rate BAfoeG

<i>PR(Enrollment)</i>	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Max. Rate)	-.0017*** (.0004)	.0001 (.0004)	.0010** (.0004)	.0010** (.0004)	.0011** (.0004)	.0011** (.0004)	.0013*** (.0004)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
N	28811	28056	28811	28811	28811	28811	26547
Cluster	9081	8726	9081	9081	9081	9081	8909
R^2	.0006	.2056	.0003	.0007	.0052	.0053	.0098
Prob > F	.0001	.0000	.0184	.0166	.0000	.0000	.0000

Robust Std. Errors in Parantheses (clustered on ID); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the estimated effect of Real BAfoeG (Max. Rate) on the probability to enroll. (1) is a baseline OLS estimation without controls, while (2) contains the set of individual controls: gross income (T-1), HH with parents, age, age², parental income, apprenticeship (last year; current year & general), first generation, migration background, siblings, partner, children, living in the city, sex, state and east Germany. (3)–(7) are the estimations in a fixed effects model including individual fixed effects.

While an initial OLS estimation, without any controls, even suggests a negative effect ($\hat{\beta} = -.0017$; $p < .01$), it is observable that this vanishes when adding potential controls on the individual level ($\hat{\beta} = .0001$; $p = \text{ns}$). However, as this model doesn't adequately control for unobserved heterogeneity, the difference in the effect of interest to the FE estimations ($\hat{\beta} = .0010$; $p < .05$) is visible. Such an effect would suggest that an increase of the individual max. rate before any deductions of 1 % leads on average to an increase in the likelihood of enrollment by 0.1 pp.

This effect is statistically significant at the 5 % level in the initial specification without potential further controls. However, adding further controls, which capture within changes such as gross income and the living situation with parents ($\hat{\beta} = .0010$; $p < .05$), and whether the person did an apprenticeship this or last year to account for higher entry probability during this stage of life ($\hat{\beta} = .0011$; $p < .05$), does not significantly impact the precision of the marginal effect but rather improves the overall model and potential predictive performance. In (6), the parental log income is added, which does not lead to a change in β nor R^2 , despite the additional optimization dimension. This provides a first indication that within changes in income of the parents might not influence the students' behavior.⁹ Adding the health status significantly improves the overall model performance and also slightly raises the effect of max. rate ($\hat{\beta} = .0013$; $p < .01$). Yet, it remains unclear if this is driven by the dropped sample of 2,264 observations.

Economically this effect, which is rather correlational than causal, can also be considered significant. Assuming a student living not at home and a change of 1000 €, which is approx. a 10 %. Hence, the model with FE would suggest an increase in enrollment probability of 1-1.3 pp. This lies in the range of the few previous estimates of 0.8 pp in Germany of Lauer (2002) and 1.35 pp in Denmark (Nielsen et al., 2010).

The micro-simulation approach used in this thesis offers an advantage: it allows to estimate the otherwise unobservable BAfoeG unconditional on the working decision (i.e. mechanical BAfoeG). Hence, we can differentiate between potential receivers (mechanical BAfoeG > 0) and non-receivers in both groups, students and non-students. Table 3 shows this differentiation and, additionally, differentiation between age groups.

It is observable that in the model with FE and all potential controls, the initial effect of 1.1 percentage points increases to 2.4 percentage points for individuals under 25 ($\hat{\beta} = .0024$; $p < .05$), 4.0 percentage points for those under 23 ($\hat{\beta} = .0040$; $p < .05$), and even 10.1 percentage points for those under 21 ($\hat{\beta} = .0101$; $p < .01$), given a 10 % change. On a broader level, this suggests that individuals are more elastic in their response to financial incentives right after finishing their education. This finding supports the path dependency argument, which indicates that once an individual's trajectory is set, it becomes more fixed and less likely to change (also indirectly visible in Figure 4). However, an increase of 10.1 pp seems unexpectedly high compared to the US estimates of 5 pp, which could be seen as upper bound estimates. One potential source of bias could be that some individuals considered by the FE estimation are only observed at a single point in time. This is because it is possible for students to graduate high school at age 20.

In contrast, columns (4) to (7) display the differentiation for two subgroups: non-BAfoeG recipients (row 1) and BAfoeG recipients (row 1 + row 2). The positive effect on students' demand by the max. rate is observed primarily in the non-recipient group ($\hat{\beta} = .0035$; $p < .01$). However, this positive effect is negated for BAfoeG recipients, where the effect is negative ($\hat{\beta} = -.0037$; $p < .01$). This (at first) counterintuitive result may be attributed to one of three possible explanations: a) model misspecification, b) negative externalities, or c) misperception of BAfoeG. The first issue, model misspecification, is straightforward. Second, negative externalities might arise if the maximum rate - as publicly discussed value - affects the application market. Increased market tightness could lead to more applications from both groups, potentially disadvantaging those in lower economic brackets if there is a correlation between economic status and grades. Finally, misperception about whether one receives BAfoeG and the amount could bias the distinction between the two groups.

⁹This argument is important w.r.t. the use of mechanical BAfoeG as an instrument.

Table 3: Enrollment: FE - Max. Rate, Specifications Age & Treated

<i>PR(Enrollment)</i>	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Max. Rate)	.0024** (.0009)	.0040*** (.0013)	.0101*** (.0023)	.0035*** (.0008)	.0053*** (.0016)	.0076*** (.0021)	.0127*** (.0034)
Real BAfoeG (Max. Rate) \times Simulated Treament				-.0037*** (.0009)	-.0048*** (.0018)	-.006** (.0024)	-.005 (.0043)
<i>Specification</i>							
Age	< 25	< 23	< 21		< 25	< 23	< 21
Gross Income (Main Job, T-1)	✓	✓	✓	✓	✓	✓	✓
HH with Parents	✓	✓	✓	✓	✓	✓	✓
Apprenticeship (This Year)	✓	✓	✓	✓	✓	✓	✓
Apprenticeship (Last Year)	✓	✓	✓	✓	✓	✓	✓
Parental Log. Income	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓
N	15100	11210	6060	28811	15100	11210	6060
Cluster	6656	5860	3943	9081	6656	5860	3943
R^2	.0063	.0089	.0290	.0064	.0072	.0102	.0297
Prob > F	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Robust Std. Errors in Parantheses (clustered on ID); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note:

The argument about misperception w.r.t. BAfoeG is also evident in [Table 4](#). When using the mechanical variation instead of the communicated maximum rate of BAfoeG, the null effect cannot be falsified, with even a negative sign in most of the specification. Although the effect is so economically small that it is negligible. This suggests that actual individual monetary differences from changes in BAfoeG do not seem to drive the decision to enroll. This null effect persists across further specifications leading to the conclusion that it is not an anomaly. The most plausible explanation is that students are unaware of these individual differences between years.

To summarize, in the model with a FE estimation using BAfoeG max. rate a positive, both economically and statistical economic effect is visible on enrollment in range of 1-1.3 pp. Further specifications of this model indicate that this relationship is more pronounced for younger individuals and that is most prominently affects non-recipients. In the model with FE estimation using mechanical BAfoeG, which can simulate for students and non-students at any time point, no effect of this actual within differences are visible. Yet, one has to be aware that in this setup the relationship is rather correlational than causal.

Table 4: Enrollment: OLS/FE - Mechanical BAfoeG

<i>PR(Enrollment)</i>	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Mechanical, in 100 €)	-.0177*** (.0008)	-.0002 (.0010)	-.0001 (.0010)	-.0006 (.0010)	-.0004 (.0010)	-0.0005 (.0010)	.0000 (.0010)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
N	28811	28056	28811	28811	28811	28811	26547
Cluster	9081	8726	9081	9081	9081	9081	8909
R^2	.0181	.2056	.0000	.0004	.0049	.0049	.0092
Prob > F	.0001	.0000	.9308	.1422	.0000	.0000	.0000

Robust Std. Errors in Parantheses (clustered on ID); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the estimated effect of Real BAfoeG (Mechanical, in 100 €) on the probability to enroll. (1) is a baseline OLS estimation without controls, while (2) contains the set of individual controls: gross income (T-1), HH with parents, age, age², parental income, apprenticeship (last year; current year & general), first generation, migration background, siblings, partner, children, living in the city, sex, state and east Germany. (3)–(7) are the estimations in a fixed effects model including individual fixed effects.

4.2 Non-Take-Up

The main argument for non-take-up is that the BAfoeG amount and non-take-up are inversely related, i.e. students with lower BAfoeG amounts are more likely to not take up BAfoeG, either due to incomplete information or bureaucratic reasons (Herber and Kalinowski, 2019). As shown in Table 5, there is an indication of this inverse relationship. The estimated average marginal effect of a 100 € increase in simulated BAfoeG is a 3.18 percentage point decrease in the non-take-up probability in the baseline specification of a pooled probit estimation ($\hat{\beta} = .0318$; $p < .01$). After adding further controls, the average marginal effect in this pooled probit estimations suggests a decrease in the range of 2.54–2.74 percentage points, depending on the specification.

One should be aware that including parental income in the same regression as (simulated) BAfoeG carries a risk of multicollinearity, as simulated BAfoeG is a function of parental income and, thus, captures similar variations, though in an inverse form. This issue is visible in specifications (2)–(4). Although income was not included directly as a continuous variable, using income categories (parental income quartiles) instead of simulated BAfoeG indicates that the second ($\hat{\beta} = .1308$; $p < .05$) and third income quartiles ($\hat{\beta} = .1456$; $p = ns$) have a higher probability of non-take-up. The non-significance of the latter effect might be due to the small sample size. However, when simulated BAfoeG is included,

both effects reverse, showing the shared variation problem. Since the average marginal effect (+0.0020) and the Pseudo- R^2 (+0.0001) increase only slightly, income is excluded from further models. This exclusion does not affect other average marginal effects, such as those for first-generation students or individuals with a migration background as visible through the specifications.

Table 5: Non-Take-Up: Pooled Probit & IV-Probit

<i>PR(Non-Take-Up)</i>	(1)		(2)		(3)		(4)		(5)	
	Probit	dydx	Probit	dydx	Probit	dydx	Probit	dydx	IV-Probit	dydx
Real BAfoeG (Simulated, in 100 €)	-.0839*** (.0158)	-.0318*** (.0058)	-.0698*** (.0171)	-.0254*** (.0062)			-.0752*** (.0201)	-.0274*** (.0072)	-.0338* (.0202)	-.0129* (.0075)
2. Quartile Parental Income					.1308** (.0571)	.0479** (.0208)	-.0118 (.0651)	-.0043 (.0237)		
3. Quartile Parental Income					.1456 (.1252)	.0532 (.0451)	-.098 (.1369)	-.0359 (.0504)		
First Generation	-.1408** (.0602)	-.0535** (.0227)	-.2048*** (.0611)	-.0746*** (.0221)	-.2153*** (.0614)	-.0787*** (.0223)	-.2075*** (.0616)	-.0756*** (.0223)	-.2190*** (.0612)	-.0799*** (.0226)
Migration Background	.0459 (.0613)	.0174 (.0233)	-.0953 (.0656)	-.0347 (.0238)	-.1120* (.0653)	-.0410* (.0238)	-.0955 (.0657)	-.0348 (.0239)	-.1112* (.0657)	-.0404* (.0240)
Age (Centered at 23)			✓		✓		✓		✓	
Apprenticeship			✓		✓		✓		✓	
Sex			✓		✓		✓		✓	
Living in City			✓		✓		✓		✓	
Living with Parents			✓		✓		✓		✓	
East Germany			✓		✓		✓		✓	
Siblings			✓		✓		✓		✓	
Year (Dummies)	✓		✓		✓		✓		✓	
N	4054		3930		3929		3929		3930	
Pseudo- R^2	.0201		.0573		.0535		.0574			
Wald χ^2	66.6764		158.6455		150.1893		158.3297		144.68	
Baseline predicted probability	.5388		.5974		.5971		.5973			
Wald Test									15.31	
Prob. > χ^2									.0001	
Instrument (First Stage)									.0091*** (.0001)	

Clustered Std. Errors in Parantheses (on ID); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The simulated mech. BAfoeG variation is used as an instrument. Regression (1) & (2) are baseline regressions with and without controls. (2)–(4) indicate the issue of including both parental income and BAfoeG. In (5) the instrument is used. As visible the marginal effect of interest is significantly smaller in absolute values. The SE is originally .000065 heavily rounded to .0001 with an unrounded effect of .00011.

Through the first pooled probit specifications, the presented results for BAfoeG's effect, the baseline predicted probability, and the baseline effects of first generation and migration background are in line with [Herber and Kalinowski \(2019\)](#) and fairly similar. Their analysis is more nuanced with respect to potential covariates like risk preference or experience with BAfoeG's bureaucracy. However, using mechanical BAfoeG as an instrument, and thus relying solely on exogenous variation, leads to a notable difference. While the average marginal effect of BAfoeG remains in the same range for [Herber and Kalinowski \(2019\)](#), it decreases in absolute value to -0.0129 ($p < 0.10$) here, which can barely be considered economically significant. This suggests a much weaker inverse relationship than anticipated, potentially driven by two factors. Either the strong negative relationship visible in the pooled probit estimations is driven by the labor supply decisions of recipients who receive smaller amounts, which are insufficient, or the misperception about BAfoeG reception effects not only in the group around the cutoff but affects all groups.

4.3 Labor Supply

The main argument regarding labor supply is that higher BAfoeG incentivizes a decrease in labor supply, as all income streams of the students can be considered substitutes. However, as shown in Table 6, a negative incentive effect is observed across all specifications. In the pooled regression, the average marginal effect is similar in both OLS estimation within a LPM ($\hat{\beta} = -.0401$; $p < .01$) and probit estimation ($\hat{\beta} = -.0398$; $p < .01$), and slightly higher in absolute terms compared to the probit estimation without controls ($\hat{\beta} = -.0364$; $p < .01$). These correlational results suggest that for every 100 € increase in BAfoeG, students' labor supply decreases by approximately 4 percentage points. This can be considered economically significant since a 4 pp change for a general labor supply participation of 49 % on average reflects a change of roughly 8 %.

Yet, using mechanical BAfoeG as an instrument in the LPM shows that the effect size is only 37.5 % ($\hat{\beta} = -.0150$; $p < .01$) or 44.8 % ($\hat{\beta} = -.0179$; $p < .01$) of the initial effect observed in the endogenous model. However, it still remains negative and statistically significant suggesting that a negative labor supply effect still exists despite accounting for the exogenous variation in BAfoeG. If the difference is attributed solely to simultaneity, it further suggests that relaxing the constraint of the student's own income could potentially weaken the negative incentive effects of increased means-tested student aid.

Looking onto Table 12 (Appendix), a similar picture is visible for the intensive margin, i.e. for those students who work. While the initial pooled specification suggest an effect between -1.4 hrs. ($p < .01$) -1.6 hrs ($p < .01$) for a 100 € increase in BAfoeG, the IV setup with mechanical BAfoeG as instrument suggests that hours only decrease by between 0.2 hrs. (no year dummies; $p < .10$) and 0.3 hrs. (with year dummies; $p < .10$).

Assuming an average hourly wage of 14 € for students, this implies that in the observed (endogenous) scenario, a 100 € increase in BAfoeG leads to a reduction in labor supply equivalent to 85–97 €. Consequently, the student is only slightly better off in purely monetary terms. However, in the IV setup, which captures the purely exogenous variation, the labor supply reduction is only 12–18 €. If this difference in estimated effects is attributed solely to simultaneity and not to other unobserved factors, it suggests that combining an increase in BAfoeG with a relaxation of the own income deduction could increase the students' financial resources more sustainable.

In summary, this analysis indicates that higher BAfoeG generally reduces student labor supply, with a negative incentive effect observed across all specifications as well as for the intensive and extensive margin. A high share of this observed negative effect is not visible in the IV setup, potentially suggesting that it is driven by endogeneity.

Table 6: Labor Supply - Extensive Margin: Pooled Probit, OLS & IV

<i>PR(Labor Supply)</i>	(1)		(2)		(3)	(4)	(5)
	Probit	dydx	Probit	dydx	OLS	IV	IV
Real BAfoeG (Simulated, in 100 €)	-.0926*** (.009)	-.0364*** (.0035)	-.106*** (.0096)	-.0398*** (.0035)	-.0401*** (.0035)	-.0150*** (.0045)	-.0179*** (.0045)
First Generation			.0968*** (.042)	.0363*** (.0158)	.0361*** (.0158)	.0107 (.0161)	.0101 (.0160)
Migration Background			-.0928** (.042)	-.0348** (.0158)	-.0345** (.0158)	-.0562*** (.0161)	-.0596*** (.016)
Apprenticeship			✓		✓	✓	✓
Age			✓		✓	✓	✓
Sex			✓		✓	✓	✓
Living in City			✓		✓	✓	✓
Living with Parents			✓		✓	✓	✓
East Germany			✓		✓	✓	✓
Siblings			✓		✓	✓	✓
Year (Dummies)							✓
N	12589		12589		12589	12589	12589
Cluster	3824		3824		3824	3824	3824
Pseudo- R^2	.0126		.0551				
R^2					.0739	.0669	.0742
Wald Chi ²	105.5566		492.9869			431.93	539.87
RMSE					.4800	.4800	.4800
Baseline predicted probability	.4896		.4899		.5442	.524	.5178
Instrument (First Stage)						.0073*** (.0001)	.0074*** (.0001)

Robust Std. Errors in Parantheses (clustered on ID); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: (1) is a baseline probit, without any controls. (2) introduces the respective controls. (3) shows that, given the same controls, probit and LPM yield similar results. In the IV setup (4) & (5) the coef. of interest is in absolute values sign. smaller.

5 Discussion and Limitations

Enrollment:

Time: Yes Placebo: NO Grant-Loan-Share: NO Average Wage instead of Inflation:

Robustnesschecks (Placebo, Different Years, Grant-Loan-Share,...) & Treatment Heterogeneity

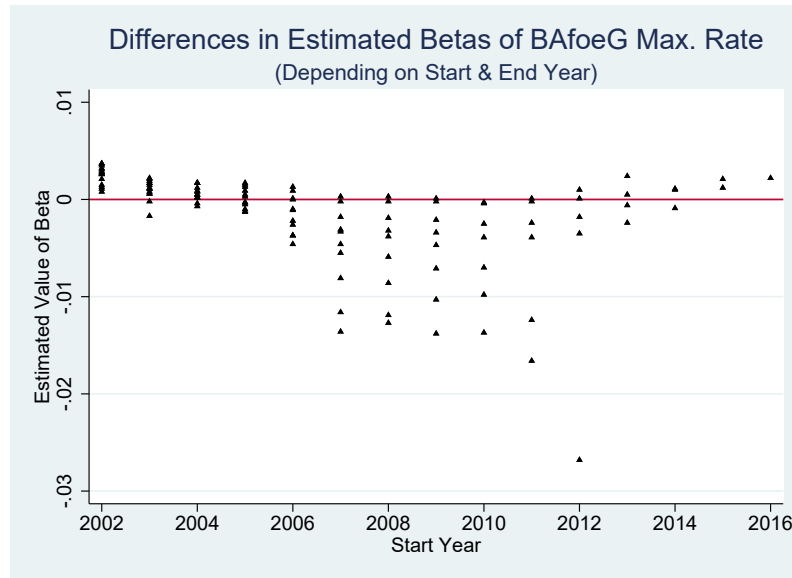


Figure 7: Differences in Estimated Betas in the Model with FE Estimation depending on Start- & End Year

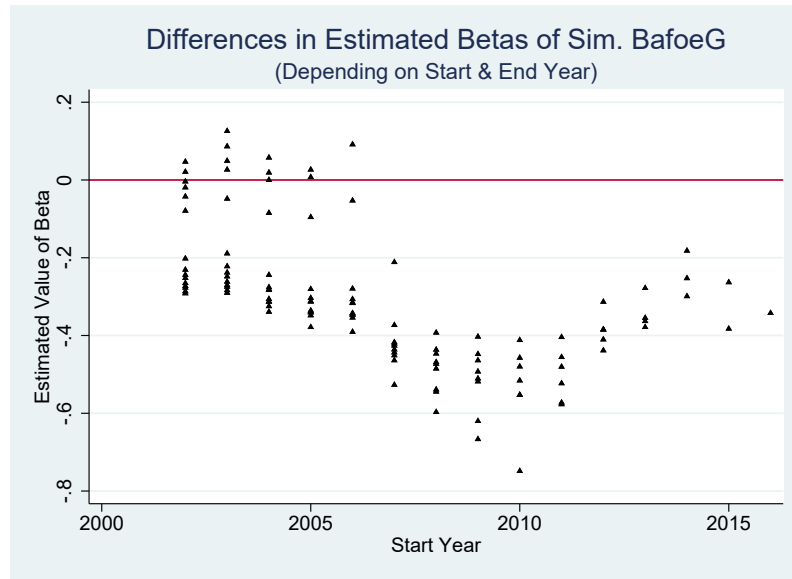


Figure 8: Differences in Estimated Betas in the Model with IV Estimation depending on Start- & End Year

- The forgotten parameter: The "Pay-Back-Cap"

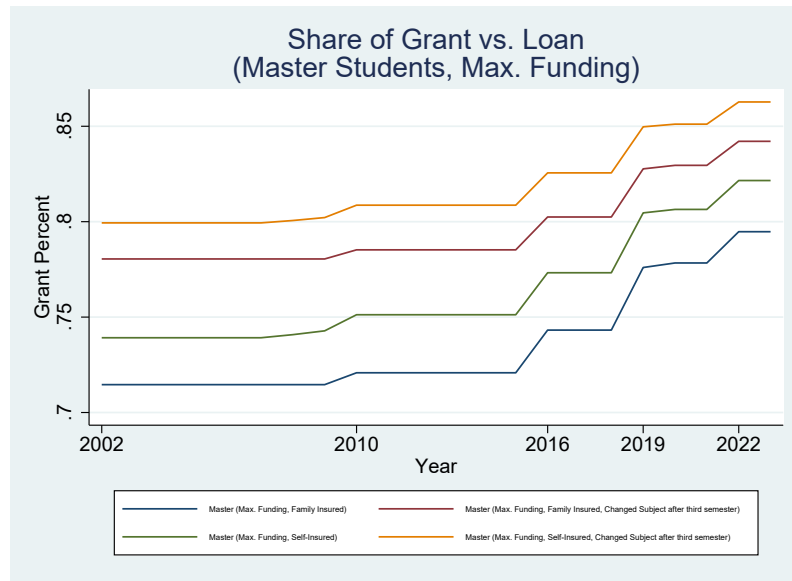


Figure 9: Grant- vs. Loan-Share in Different Scenarios

- Search & Matching in this thesis excluded.
- Causal Diagram to highlight the imposed orthogonality assumptions.
- Treatment Heterogeneity

6 Summary and Concluding Remarks

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A Further Figures

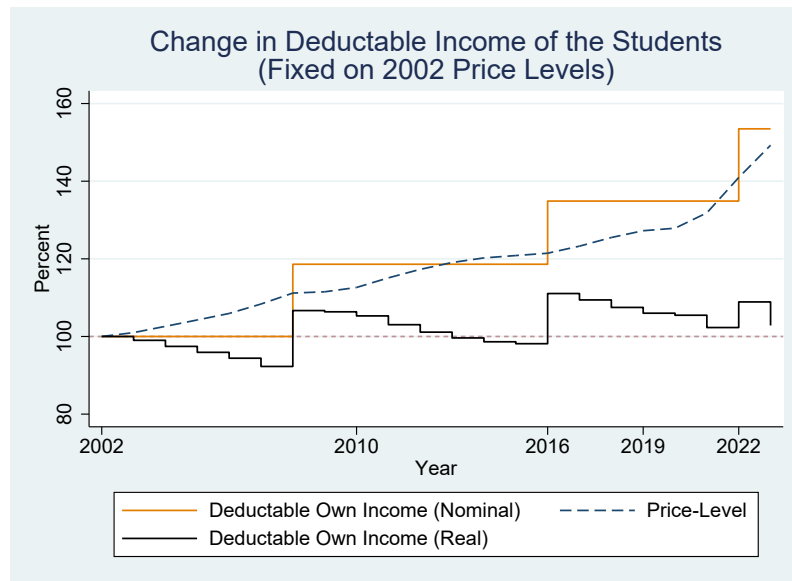


Figure 10: Paramter Change over Time in Deductible Income of the Students

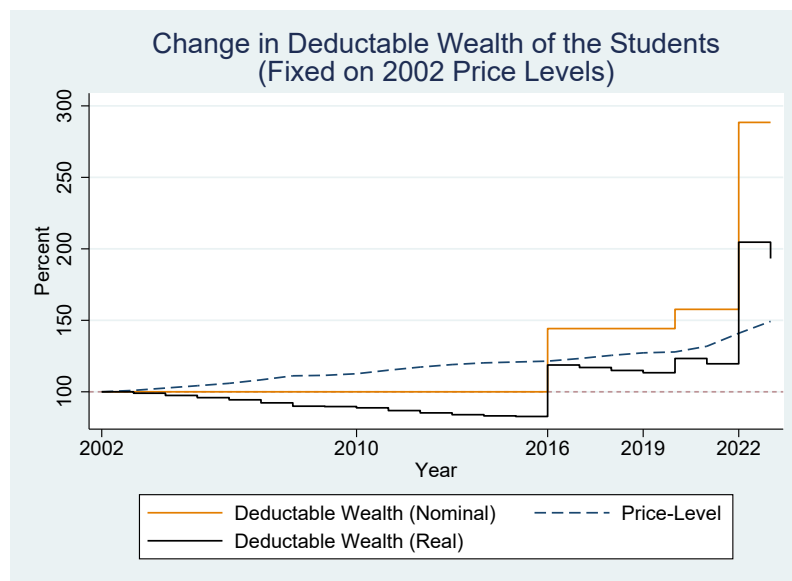


Figure 11: Paramter Change over Time in Deductible Wealth of the Students

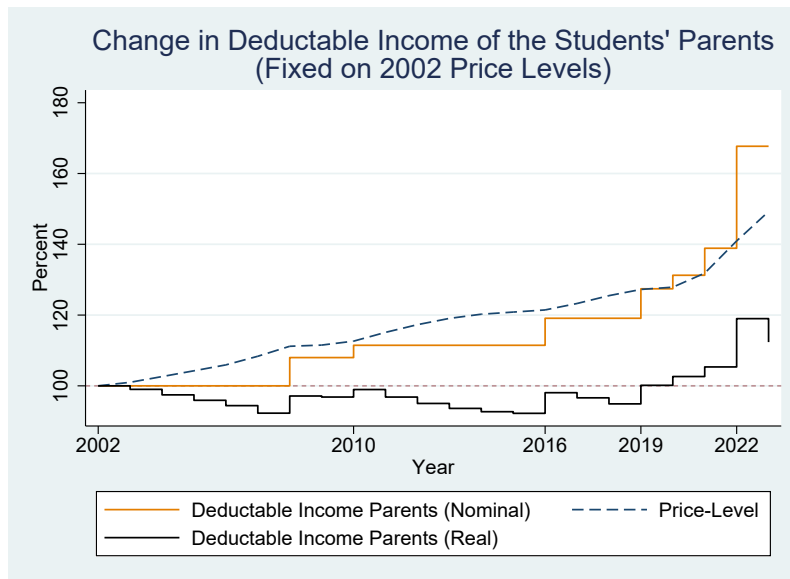


Figure 12: Paramter Change over Time in Deductable Income of the Students' Parents

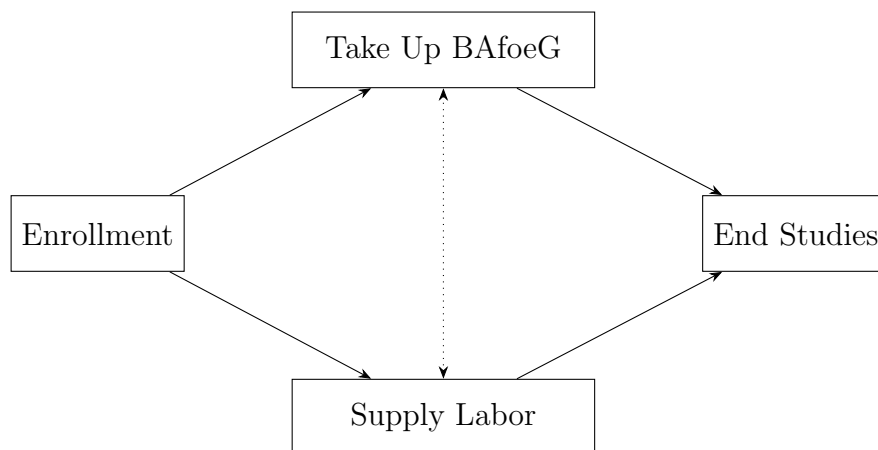


Figure 13: Students' Decision Nodes which might be affected by BAfoeG

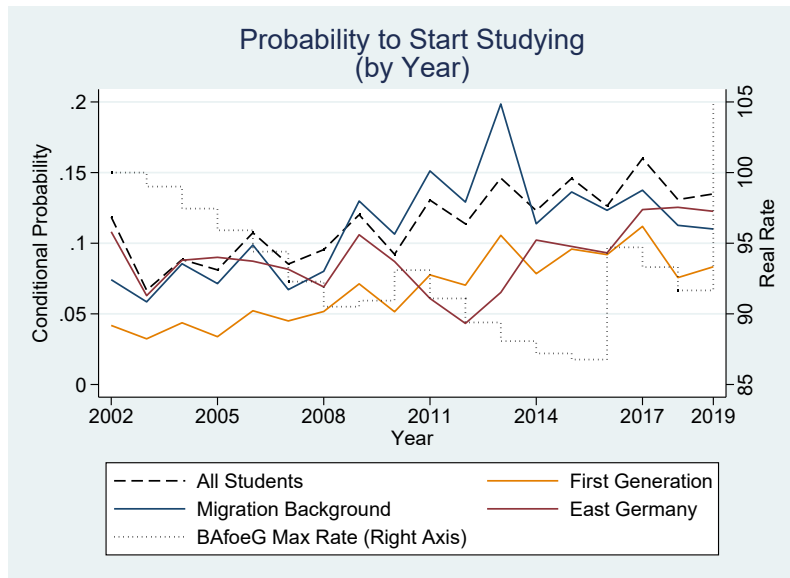


Figure 14: Probability to Start Studying by Year & Subgroup

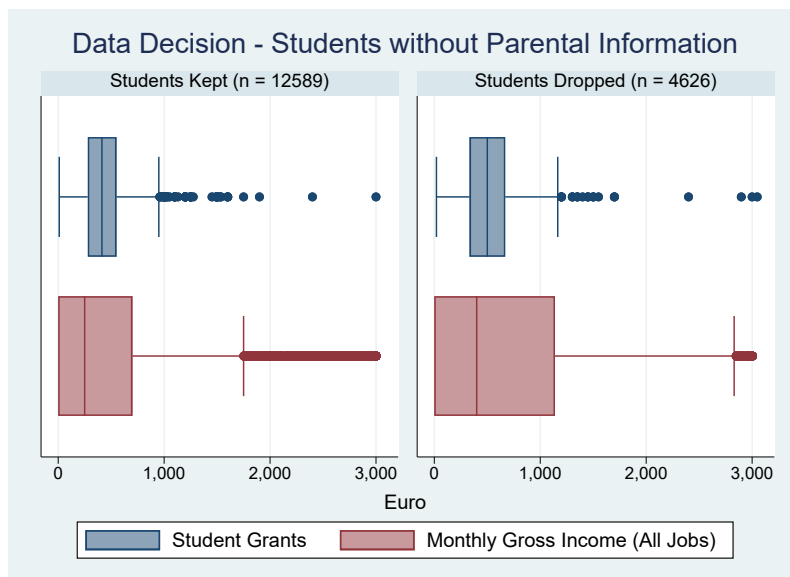


Figure 15: Income & Student Grants; Kept vs. Dropped Students

B Further Tables

Table 7: Overview of BAfoeG Variables

Variable	Description
BAfoeG Max. Rate	Individual max. value before deductions and allowances (considered as rate; based on § 12 BAföG)
Mechanical BAfoeG	Individual BAfoeG value without deduction of own income
Simulated BAfoeG	Individual BAfoeG value with deduction of own income
BAfoeG / Student Grant	This is based on the SOEP and includes the self-reported numbers. However, as it includes both BAfoeG and student grants in the question combined with a lot of missings, it is not used.

Table 8: Share of BAfoeG Recipients per Year - Actual vs. Simulated

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
<i>Received Student Grants (actual)</i>	12589	.2361	.4247	0	1
- 2002	589	.2309	.4218	0	1
- 2003	601	.2696	.4441	0	1
- 2004	660	.2591	.4385	0	1
- 2005	633	.2243	.4175	0	1
- 2006	641	.234	.4237	0	1
- 2007	614	.2117	.4089	0	1
- 2008	607	.2273	.4195	0	1
- 2009	599	.2321	.4225	0	1
- 2010	615	.2325	.4228	0	1
- 2011	644	.264	.4411	0	1
- 2012	637	.2873	.4529	0	1
- 2013	772	.2798	.4492	0	1
- 2014	764	.2421	.4287	0	1
- 2015	812	.2389	.4267	0	1
- 2016	794	.2418	.4285	0	1
- 2017	886	.2167	.4122	0	1
- 2018	890	.191	.3933	0	1
- 2019	831	.1913	.3936	0	1
<i>BAfoeG (simulated)</i>	12589	.3220	.4673	0	1
- 2002	589	.3379	.4734	0	1
- 2003	601	.3411	.4745	0	1
- 2004	660	.2894	.4538	0	1
- 2005	633	.2717	.4452	0	1
- 2006	641	.259	.4384	0	1
- 2007	614	.2492	.4329	0	1
- 2008	607	.2685	.4436	0	1
- 2009	599	.2805	.4496	0	1
- 2010	615	.3122	.4638	0	1
- 2011	644	.3323	.4714	0	1
- 2012	637	.3312	.471	0	1
- 2013	772	.3795	.4856	0	1
- 2014	764	.3442	.4754	0	1
- 2015	812	.3387	.4735	0	1
- 2016	794	.3766	.4848	0	1
- 2017	886	.3533	.4783	0	1
- 2018	890	.3371	.473	0	1
- 2019	831	.3333	.4717	0	1

Note: Student Grants include state funding (BAfoeG) as well as other forms of stipends. BAfoeG amounts are calculated under the assumption of optimal behavior and always assume an application is made if the amount is greater than zero. Therefore, these figures may be higher than the actual amounts received.

Table 9: Overview of Core Variables and its SOEP Origin

Variable	Description
Age	Derived from variable D11101, representing the age of the participant in years.
Apprenticeship (Dummy)	Did an Apprenticeship overall, this year or last year. This is gathered by <code>kal1c00i</code> with $i \in [1,12]$.
BAfoeG (€, Mth.)	Indicates how much BAfoeG support the student received, based on variable <code>kal2k03.v2</code> . However, one has to be careful, as this includes in some waves "student grants" and not specifically BAfoeG, meaning merit-based or private grants could bias this upwards. Further, there are a lot of missings for students, who are supposed to have a value there (approx 20 %) and some values don't survive a plausability check.
BAfoeG (Dummy)	Indicates whether the participant received BAfoeG support, based on variables <code>plc0170</code> and <code>plc0169.v1</code> . Variable <code>pab0037</code> is excluded as it is only relevant for data pre-2000. However, one has to be careful, as this includes in some waves "student grants" and not specifically BAfoeG, meaning merit-based or private grants could bias this upwards.
Educational Status (Ordinal)	Represents the highest level of education attained by the participant, based on variables <code>plg0078.h</code> and <code>pgisced11</code> . Data is forward imputed between waves in the panel. This is based on the ICED Scale with low, middle and high education.
Eligible for BAfoeG (Ordinal)	Asses Eligibility based on whether the participant is currently a student and resides within Germany (as indicated by <code>plj0709</code>). Eligibility also considers the participant's age, ensuring they are under 35 years old. Furthermore, adjustments are made based on the Year in University and Educational Level to exclude cases where it is certain that the standard period of study is not met.
First Gen (Dummy)	Neither parent has a tertiary degree.
Health Status (5 Levels)	The person's self reported health status derived from <code>ple0008</code> . From 1 "very good" to 5 "bad".
HH Constellation	Describes the composition of the participant's household or family structure, calculated from variables <code>d11104</code> , <code>pgpartz</code> , <code>pid</code> , and <code>parid</code> .
HH with Parents (Ordinal)	Living in the same household with parents. This is initially derived by '11104, <code>pgpartz</code> , <code>hid</code> , <code>pid</code> , and <code>parid</code> . Yet, this is very specific for the soep, there is a distinction between reported household and factual living adress. For the BAfoeG the latter mattes. Hence, this is overreporting students living at home (as visible in Herber and Kalinowski (2019)). Hence, this is corrected by any means possible. First, if reported state of mum and dad differ fromt he students reported state, then is rural or not does not match for both cases, then over the current location of the dad (<code>fcurrlloc</code>) and mum (<code>mcurrlloc</code>)
Income (€, Mth.)	Monthly Gross Income. All income types within the soep are considered. This means: <code>plc0141</code> <code>plc0142.h</code> <code>plc0070.h</code> <code>plc0186</code> <code>plc0187</code> <code>plc0189.h</code> <code>plc0190.v1</code> <code>plc0190.v2</code> <code>hlc0045.h</code> <code>hlc0081</code> <code>hlc0082.h</code> <code>pglabgro</code> <code>pgsndjob</code> <code>pgsndjob1</code> <code>pgsndjob2</code> <code>pgsndjob3</code> <code>divdy</code> <code>lossc</code> <code>renty</code> <code>lossr</code> <code>nursh</code> <code>ssold</code> <code>alg2</code> <code>adchb</code> <code>chspt</code> <code>ielse</code> <code>imaty</code> <code>imilt</code> <code>istuy</code> <code>house</code> <code>ijob1</code> <code>ijob2</code> <code>iself</code> <code>il3ly</code> <code>il4ly</code> <code>ixmas</code> <code>iholy</code> <code>igray</code> <code>iothy</code> <code>iwdy</code> <code>ioldy</code> <code>icomp</code> <code>iprvp</code> <code>igrv1</code> <code>igrv2</code> <code>iciv1</code> <code>iciv2</code> <code>iwar1</code> <code>iwar2</code> <code>iguv1</code> <code>iguv2</code> <code>ivbl1</code> <code>ivbl2</code> <code>icom1</code> <code>icom2</code> <code>iprv1</code> <code>iprv2</code> <code>ison1</code> <code>ison2</code> <code>iunby</code> <code>ispou</code> <code>ichsu</code> <code>ialim</code> <code>iachm</code> <code>i11102</code> <code>i11110</code> <code>kal2a02</code> <code>kal2a03.v2</code> <code>kal1h02</code> <code>kal2b02</code> <code>kal2b03.v2</code> <code>kal2c02</code> <code>kal2c03.v2</code> <code>kal2d02</code> <code>kal2d03.v2</code> <code>kal2e02</code> <code>kal2e03.v2</code> <code>kal2f02</code> <code>kal2f03.v2</code> <code>kal2k02</code> <code>kal2k03.v2</code> <code>kal2j02</code> <code>kal2j03.v2</code> <code>kall1a001.v2</code> <code>kall1a002.v2</code> <code>kall1a003.v2</code> <code>kall1a004.v2</code> <code>kall1a005.v2</code> <code>kall1a006.v2</code> <code>kall1a007.v2</code> <code>kall1a008.v2</code> <code>kall1a009.v2</code> <code>kall1a010.v2</code> <code>kall1a011.v2</code> <code>kall1a012.v2</code> <code>kall1b001</code> <code>kall1b002</code> <code>kall1b003</code> <code>kall1b004</code> <code>kall1b005</code> <code>kall1b006</code> <code>kall1b007</code> <code>kall1b008</code> <code>kall1b009</code> <code>kall1b010</code> <code>kall1b011</code> <code>kall1b012</code> . Missing values within one wave are imputed using a Heckmann correction, if the needed variables are given. W.r.t. BAfoeG it is obviously differentiated between the income types. Specified in Section 2 .
Labor Supply	Weekly hrs. Worked. This is implicitly derived from <code>pgtatzeit</code> <code>pguebstd</code> <code>plb0176.h</code> <code>plb0186.h</code> <code>plb0197</code> <code>plb0198</code> <code>plb0573</code> <code>plb0632</code> <code>plb0633</code> <code>plb0634</code> . It is assumed that every person in the model has 80 hrs. per week. Hence, we drop any exceeding values. It combines working hours for different jobs (e.g. first and second job).
Living in City (Ordinal)	Specifies whether the participant resides in a rural or non-rural area, based on variable <code>regtyp</code> . If missing, imputed from <code>t-1</code> or <code>t+1</code> .
Male (Dummy)	Indicates the participant's sex, with 0 representing female and 1 representing male. Data is imputed over time and, if totally missing, randomly assignment as 0 or 1. Changes in reported gender are not preserved; only the latest entry is used, overwriting any previous entries.
Migration Background (Dummy)	First or second degree migration background, based on <code>pid/mid</code> and <code>migback</code> .
Partner/Marital Status (Dummy/Ordinal)	Indicates the current partnership or marital status of the participant, derived from variables <code>pid</code> , <code>parid</code> , <code>d11104</code> , and <code>pgpartz</code> .
State (& East Germany)	Indicates the specific state or region where the participant resides, derived from variables <code>bula.h</code> and <code>sampreg</code> . If missing, imputed from <code>t-1</code> or <code>t+1</code> .
Student (Dummy)	Equivalent to Glocker (2011) "If a person is observed as having studied in the months between October and March, they count as a student in the winter term (Wintersemester). Being a student in the summer term (Sommersemester) implies having studied between April and September." Based on variables <code>pab0013</code> , <code>plg0078.h</code> , <code>pgisced11</code> , <code>plg0014.v7</code> , <code>plg0014.v5</code> , <code>plg0014.v6</code> . Adjusted to exclude individuals with <code>arbeitszeit.w.akt</code> \geq 40 hours per week. Additional corrections for eligibility for winter and summer terms, and high school completion status.
Tax Class (Ordinal)	This comes from "steuerklasse". However, if this is not given, we assign a Tax class under optimal behavior w.r.t. III and V this is relevant. Still, this might be biased as you actively have to decide it (see e.g. the argument in Buettner et al., 2019).
University Type (Ordinal)	Represents the type of University attended by the student. Includes students who are currently studying, based on variables <code>plg0014.v7</code> , <code>plg0014.v6</code> , and <code>plg0014.v5</code> . Missing data is imputed from the last waves or assumes normal university attendance. Excludes individuals pursuing promotions.
Year in University	Counting years since reported studying. This count only includes periods when the student was actively enrolled in studies.

Table 10: Summary Statistics Non-Students (2002-2019)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
<i>Individual Characteristics:</i>					
Age	25458	25.7247	5.0839	17	35
Male	25458	.5171	.4997	0	1
Migration Background	25458	.2708	.4444	0	1
First Gen	25458	.6952	.4603	0	1
<i>Income:</i>					
Inc. Student (€, Gross, Mth.)	25458	1315.5583	1301.5073	0	49000
Labor Supply	25458	.7996	.4003	0	1
Labor Supply (Weekly Hours)	25458	27.4549	17.4159	0	80
Inc. Father (€, Gross, Mth.)	25458	2144.1482	3181.3766	0	104000
Inc. Mother (€, Gross, Mth.)	25458	1050.8017	1345.8818	0	25000
<i>BAfoeG:</i>					
BAfoeG (Mechanical)	25458	.6597	.4738	0	1
BAfoeG (Mechanical, €, Mth.)	16795	453.3889	226.5455	10	1553

Note: A person is considered a non-student if they are under 35 years old, have earned the right to study, but are not studying in the respective year and have not finished any post-secondary degree.

Table 11: Enrollment: Pooled OLS & Probit - Max. Rate

$PR(Enrollment)$	(1) Probit	dydx	(2) OLS
Real BAfoeG (Max. Rate)	-.0021 (.0024)	-.0004 (.0004)	-.0004 (.0004)
First Generation	-.6151*** (.0237)	-.1028*** (.0039)	-.1231*** (.0051)
Migration Background	-.0349 (.0269)	-.0058 (.0045)	-.0048 (.0048)
East Germany	-.3191*** (.0306)	-.0533*** (.0051)	-.0631*** (.005)
Gross Income T-1 (Main Job)	-.0005*** (0)	-.0001*** (0)	-.0001*** (0)
N	28811		28811
R^2			.0992
Pseudo- R^2	.1562		
RMSE			.3000
Wald Chi ²	1847.82		

Cluster Robust Std. Errors in Parantheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This shows that an OLS within a LPM yields similar marginal effects for the real BAfoeG Max. Rate than Probit.

Table 12: Labor Supply - Intensive Margin: Pooled OLS & IV

<i>Labor Supply (Hrs)</i>	(1) OLS	(2) OLS	(3) IV	(4) IV
Real BAfoeG (Simulated, in 100 €)	-1.4224*** (.0733)	-1.6306*** (.0808)	-.2084* (.1172)	-.2917** (.1151)
First Generation		2.2152*** (.3644)	.7791** (.371)	.7618** (.3677)
Migration Background		-.4899 (.3644)	-1.7223*** (.371)	-1.8529*** (.3677)
Apprenticeship		✓	✓	✓
Age		✓	✓	✓
Sex		✓	✓	✓
Living in City		✓	✓	✓
Living with Parents		✓	✓	✓
East Germany		✓	✓	✓
Siblings		✓	✓	✓
Year (Dummies)				✓
N	12589	12589	12589	12589
Cluster	3824	3824	3824	3824
R^2	.0363	.1323	.1014	.1126
Wald Chi ²			602.31	719.15
RMSE	13.25	12.58	12.8	12.72
Instrument (First Stage)			.0073*** (.0001)	.0073*** (.0001)

Robust Std. Errors in Parantheses (clustered on ID); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note:

Table 13: Estimated Coef. onto Enrollment in Model with FE Estimation including different Start & End Points

Start	End	Estimated Coef.	Start	End	Estimated Coef.
2002	2005	.0013	2006	2016	.0009
2002	2006	.0021	2006	2017	-.001
2002	2007	.0032***	2006	2018	-.0022***
2002	2008	.0037***	2006	2019	.0001
2002	2009	.0037***	2007	2010	-.0046**
2002	2010	.0035***	2007	2011	-.0136***
2002	2011	.0031***	2007	2012	-.0116***
2002	2012	.0027***	2007	2013	-.0081***
2002	2013	.0026***	2007	2014	-.0055***
2002	2014	.0026***	2007	2015	-.0033***
2002	2015	.0029***	2007	2016	.0003
2002	2016	.0028***	2007	2017	-.0018**
2002	2017	.0015***	2007	2018	-.0031***
2002	2018	.0008	2007	2019	-.0002
2002	2019	.0011**	2008	2011	-.0127***
2003	2006	-.0017	2008	2012	-.0119***
2003	2007	.0008	2008	2013	-.0086***
2003	2008	.0017**	2008	2014	-.0059***
2003	2009	.0022***	2008	2015	-.0038***
2003	2010	.0021***	2008	2016	.0003
2003	2011	.0015**	2008	2017	-.0019**
2003	2012	.0011	2008	2018	-.0032***
2003	2013	.0011	2008	2019	-.0002
2003	2014	.0012*	2009	2012	-.0138***
2003	2015	.0017***	2009	2013	-.0103***
2003	2016	.0019***	2009	2014	-.0071***
2003	2017	.0006	2009	2015	-.0047***
2003	2018	-.0002	2009	2016	.0001
2003	2019	.0006	2009	2017	-.0021**
2004	2007	-.0004	2009	2018	-.0034***
2004	2008	.0009	2009	2019	-.0002
2004	2009	.0017*	2010	2013	-.0137***
2004	2010	.0017*	2010	2014	-.0098***
2004	2011	.0008	2010	2015	-.007***
2004	2012	.0002	2010	2016	-.0004
2004	2013	.0002	2010	2017	-.0025***
2004	2014	.0005	2010	2018	-.0039***
2004	2015	.0012	2010	2019	-.0003
2004	2016	.0017***	2011	2014	-.0166***
2004	2017	.0002	2011	2015	-.0124***
2004	2018	-.0007	2011	2016	.0001
2004	2019	.0005	2011	2017	-.0024**
2005	2008	.0009	2011	2018	-.0039***
2005	2009	.0017	2011	2019	-.0002
2005	2010	.0013	2012	2015	-.0268***
2005	2011	-.0003	2012	2016	.001
2005	2012	-.0012	2012	2017	-.0018*
2005	2013	-.001	2012	2018	-.0035***
2005	2014	-.0005	2012	2019	.0001
2005	2015	.0005	2013	2016	.0024**
2005	2016	.0015**	2013	2017	-.0006
2005	2017	-.0003	2013	2018	-.0024**
2005	2018	-.0013*	2013	2019	.0005
2005	2019	.0003	2014	2017	.001
2006	2009	.0013	2014	2018	-.0009
2006	2010	.0000	2014	2019	.0011*
2006	2011	-.0037**	2015	2018	.0012
2006	2012	-.0046***	2015	2019	.0021***
2006	2013	-.0037***	2016	2019	.0022***
2006	2014	-.0026**			
2006	2015	-.0011			

Table 14: Enrollment: OLS/FE - Max. Rate – Nominal Wage change instead of VPI

<i>PR(Enrollment)</i>	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Max. Rate)	-.0004*** (.0000)	.0001 (.0000)	.0002*** (.0001)	.0002*** (.0001)	.0003*** (.0001)	.0003*** (.0001)	.0002*** (.0001)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
N	28811	28056	28811	28811	28811	28811	26547
Cluster	9081	8726	9081	9081	9081	9081	8909
R^2	.0028	.2057	.0009	.0014	.0067	.0067	.0101
Prob > F	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Robust Std. Errors in Parantheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 15: Enrollment: OLS/FE - Mechanical – Nominal Wage change instead of VPI

<i>PR(Enrollment)</i>	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Mechanical)	-.0000*** (.0000)	.0000 (.0000)	.0000 (.0000)	.0000 (.0000)	.0000 (.0000)	.0000 (.0000)	.0000 (.0000)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
N	28811	28056	28811	28811	28811	28811	26547
Cluster	9081	8726	9081	9081	9081	9081	8909
R^2	.0192	.2056	.0001	.0004	.0049	.0049	.0093
Prob > F	.0000	.0000	.8663	.1610	.0000	.0000	.0000

Robust Std. Errors in Parantheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: e.g. (1) -2e-06***, only sign effect, heavily rounded.

Table 16: Enrollment: OLS/FE - Max. Rate – With estimated Grant Share

<i>PR(Enrollment)</i>	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Max. Rate)	-.0036*** (.0005)	-.0012*** (.0004)	-.0002 (.0005)	-.0002 (.0005)	-.0001 (.0005)	-.0001 (.0005)	.0004 (.0005)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
Grant Share	✓	✓	✓	✓	✓	✓	✓
N	18423	17894	18423	18423	18423	18423	17065
Cluster	6198	5932	6198	6198	6198	6198	6028
R^2	.0271	.1753	.0005	.0017	.0056	.0056	.0093
Prob > F	.0000	.0000	.0003	.0000	.0000	.0000	.0000

Robust Std. Errors in Parantheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 17: Enrollment: OLS/FE - Max. Rate – First Generation Students

<i>PR(Enrollment)</i>	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
Real BAfoeG (Max. Rate)	-.0023*** (.0004)	-.0009** (.0004)	.0001 (.0004)	.0001 (.0004)	.0002 (.0004)	.0002 (.0004)	.0006 (.0004)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
N	19006	18503	19006	19006	19006	19006	17669
Cluster	5457	5235	5457	5457	5457	5457	5371
R^2	.0018	.1512	.0001	.0006	.0043	.0043	.0077
Prob > F	.0000	.0000	.8698	.0639	.0000	.0000	.0000

Robust Std. Errors in Parantheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 18: Enrollment: OLS/FE - Max. Rate – Migration Background

<i>PR(Enrollment)</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	FE	FE	FE	FE	FE
Real BAfoeG (Max. Rate)	-.0038*** (.0007)	-.0009 (.0007)	-.0003 (.0007)	-.0002 (.0007)	-.0002 (.0007)	-.0002 (.0007)	.0012 (.0008)
<i>Specification</i>							
Set of Individual Controls		✓					
Gross Income (Main Job, T-1)				✓	✓	✓	✓
HH with Parents				✓	✓	✓	✓
Apprenticeship (This Year)					✓	✓	✓
Apprenticeship (Last Year)					✓	✓	✓
Parental Log. Income						✓	✓
Health Status							✓
Individual FE			✓	✓	✓	✓	✓
N	7810	7574	7810	7810	7810	7810	7127
Cluster	2708	2598	2708	2708	2708	2708	2658
R^2	.0034	.1818	0.0001	.0008	.0048	.0048	.0096
Prob > F	.0000	.0000	.6208	.1625	.0009	.0020	.0004

Robust Std. Errors in Parantheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 19: Non-take-Up: Pooled & IV

	(1)	(2)	(3)	(4)
<i>Pr(Non-Take-Up)</i>	IV	IV	IV	IV
Simulated BAfoeG (Real)	-.0216** (.0102)	.0005 (.0131)	.0022 (.0185)	-.0128* (.0073)
First Generation		-.0708* (.0361)		-.0797*** (.0238)
Migration Background	-.0133 (.0318)			-.0393* (.0238)
Apprenticeship	✓	✓	✓	✓
Sex	✓	✓	✓	✓
Living in City	✓	✓	✓	✓
Living with Parents	✓	✓	✓	✓
East Germany	✓	✓	✓	✓
Siblings	✓	✓	✓	✓
Year (Dummies)	✓	✓	✓	✓
N	2132	1410	901	3930
Cluster	969	639	406	1765
R^2	.0844	.0423	.0524	.0735
Wald Chi ²	124.58	50.43	48.6	177.32
RMSE	.47	.48	.48	.47
Instrument (First Stage)	.0091*** (.0001)	.0091*** (.0002)	.0091*** (.0002)	.0091*** (.0001)

Clustered Std. Errors in Parantheses (on ID); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 20: Non-take-Up: Pooled & IV

<i>Pr(Non-Take-Up)</i>	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
Simulated BAfoeG (Real)	-.0128* (.0073)	-.0112 (.0073)	-.0096 (.0073)	-.0179** (.0091)	-.0026 (.011)
First Generation	✓	✓	✓	✓	✓
Migration Background	✓	✓	✓	✓	✓
Apprenticeship	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓
Living in City	✓	✓	✓	✓	✓
Living with Parents	✓	✓	✓	✓	✓
East Germany	✓	✓	✓	✓	✓
Siblings	✓	✓	✓	✓	✓
Year (Dummies)	✓	✓		✓	✓
Grant Share		✓			
Period	2002–2019	2002–2019	2002–2019	2002–2013	2014–2019
N	3930	3930	3930	2246	1684
Cluster	1765	1765	1765	1058	896
R^2	.0735	.0746	.0643	.0699	.0777
Wald Chi ²	177.32	184.96	140.37	106.98	91.43
RMSE	.47	.47	.48	.48	.46
Instrument (First Stage)	.0091*** (.0001)	.0090*** (.0001)	.0090*** (.0001)	.0090*** (.0001)	.0090*** (.0002)

Cluster Robust Std. Errors in Parantheses (on ID); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 21: Non-take-Up: Pooled & IV

	(1)	(2)	(3)	(4)	(5)
<i>Pr(Non-Take-Up Mechanical BAfoeG)</i>	IV	IV	IV	IV	IV
Simulated BAfoeG (Real)	-.0226*** (.0071)	-.0189*** (.0071)	-.0192*** (.0071)	-.0235*** (.0088)	-.0133 (.0104)
First Generation	✓	✓	✓	✓	✓
Migration Background	✓	✓	✓	✓	✓
Apprenticeship	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓
Living in City	✓	✓	✓	✓	✓
Living with Parents	✓	✓	✓	✓	✓
East Germany	✓	✓	✓	✓	✓
Siblings	✓	✓	✓	✓	✓
Year (Dummies)	✓	✓		✓	✓
Grant Share		✓			
Period	2002–2019	2002–2019	2002–2019	2002–2013	2014–2019
N	4978	4978	4978	2816	2162
Cluster	2054	2054	2054	1227	1066
R^2	.0750	.0759	.0659	.0718	.0761
Wald Chi ²	175.29	189.82	135.59	108.82	89.24
RMSE	.46	.46	.47	.47	.45
Instrument (First Stage)	.0083*** (.0002)	.0083*** (.0002)	.0081*** (.0002)	.0085*** (.0002)	.0080*** (.0002)

Cluster Robust Std. Errors in Parantheses (on ID)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 22: Labor Supply – Intensive Margin: Pooled IV for Different Subgroups

<i>Labor Supply (Hrs)</i>	(1) IV	(2) IV	(3) IV	(4) IV
Simulated BAfoeG (Real)	-.4259** (.181)	-.1925 (.1745)	-.2733 (.2507)	-.2917** (.1151)
First Generation		-.0426 (.5893)		.7618** (.3677)
Migration Background	-2.2491*** (.5501)			-1.8529*** (.3677)
Apprenticeship	✓	✓	✓	✓
Sex	✓	✓	✓	✓
Living in City	✓	✓	✓	✓
Living with Parents	✓	✓	✓	✓
East Germany	✓	✓	✓	✓
Siblings	✓	✓	✓	✓
Year (Dummies)	✓	✓	✓	✓
N	4274	2862	1442	12589
Cluster	1498	1004	551	3824
R^2	.1339	.101	.126	.1126
Wald Chi ²	333.5	188.39	120.75	719.15
RMSE	12.98	11.66	11.64	12.72
Instrument (First Stage)	.0073*** (.0002)	.0080*** (.0002)	.0080*** (.0003)	.0073*** (.0001)

Cluster Robust Std. Errors in Parantheses (on ID); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 23: Labor Supply – Extensive Margin: Pooled IV for Different Subgroups

<i>Pr(Labor Supply)</i>	(1) IV	(2) IV	(3) IV	(4) IV
Simulated BAfoeG (Real)	-.0269*** (.0068)	-.0216*** (.0076)	-.0322*** (.011)	-.0179*** (.0045)
First Generation		.0110 (.2653)		.0101 (.0160)
Migration Background	-.0543** (.0233)			-.0596*** (.016)
Apprenticeship	✓	✓	✓	✓
Sex	✓	✓	✓	✓
Living in City	✓	✓	✓	✓
Living with Parents	✓	✓	✓	✓
East Germany	✓	✓	✓	✓
Siblings	✓	✓	✓	✓
Year (Dummies)	✓	✓	✓	✓
N	4274	2862	1442	12589
Cluster	1498	1004	551	3824
R^2	.0954	.0729	.0974	.0742
Wald Chi ²	250.05	125.31	91.42	539.87
RMSE	.48	.48	.47	.48
Instrument (First Stage)	.0073*** (.0002)	.0080*** (.0002)	.0080*** (.0003)	.0074*** (.0001)

Cluster Robust Std. Errors in Parantheses (on ID); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 24: Labor Supply - Extensive & Intensive Margin: Differences in Instruments

	Extensive Margin		Intensive Margin	
	(1) IV	(2) IV	(3) IV	(4) IV
Simulated BAfoeG (Real)	-.0179*** (.0045)	-.0477 (.1292)	-.2917** (.1151)	-1.2972 (3.439)
Instrument	Mech. BAfoeG	Max. Value BAfoeG	Mech. BAfoeG	Max. Value BAfoeG
First Generation	✓	✓	✓	✓
Migration Background	✓	✓	✓	✓
Apprenticeship	✓	✓	✓	✓
Sex	✓	✓	✓	✓
Living in City	✓	✓	✓	✓
Living with Parents	✓	✓	✓	✓
East Germany	✓	✓	✓	✓
Siblings	✓	✓	✓	✓
Year (Dummies)	✓	✓	✓	✓
N	12589	12589	12589	12589
Cluster	3824	3824	3824	3824
R^2	.0742	.0799	.1126	.1392
Wald Chi ²	539.87	526.54	719.15	750.47
RMSE	.48	.48	12.72	12.53
Instrument (First Stage)	.0074*** (.0001)	.0054*** (.0001)	.0073*** (.0001)	.0045** (.0022)

Cluster Robust Std. Errors in Parantheses (on ID); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Table 25: Estimated Coef. onto Labor Supply (Intensive Margin) in Model with IV Estimation including different Start & End Points

Start	End	Estimated Coef.	Start	End	Estimated Coef.
2002	2005	-.0426	2006	2017	-.3443**
2002	2006	.0468	2006	2018	-.3067**
2002	2007	.0209	2006	2019	-.3541***
2002	2008	-.004	2007	2010	-.2114
2002	2009	-.0193	2007	2011	-.4511**
2002	2010	-.0793	2007	2012	-.4639**
2002	2011	-.2021	2007	2013	-.527***
2002	2012	-.231	2007	2014	-.4261**
2002	2013	-.2865**	2007	2015	-.4435***
2002	2014	-.244*	2007	2016	-.436***
2002	2015	-.2653**	2007	2017	-.4209***
2002	2016	-.2728**	2007	2018	-.3733***
2002	2017	-.2771**	2007	2019	-.4175***
2002	2018	-.252**	2008	2011	-.5445**
2002	2019	-.2917**	2008	2012	-.5391**
2003	2006	.1258	2008	2013	-.5969***
2003	2007	.0863	2008	2014	-.4729***
2003	2008	.0491	2008	2015	-.4852***
2003	2009	.0265	2008	2016	-.4686***
2003	2010	-.0483	2008	2017	-.4466***
2003	2011	-.1891	2008	2018	-.3928***
2003	2012	-.2221	2008	2019	-.4366***
2003	2013	-.2836*	2009	2012	-.6202***
2003	2014	-.2381*	2009	2013	-.6667***
2003	2015	-.2617*	2009	2014	-.5107***
2003	2016	-.2706**	2009	2015	-.5182***
2003	2017	-.2747**	2009	2016	-.4928***
2003	2018	-.2482**	2009	2017	-.464***
2003	2019	-.2903**	2009	2018	-.4031***
2004	2007	.0574	2009	2019	-.4479***
2004	2008	.0189	2010	2013	-.7486***
2004	2009	.0000	2010	2014	-.5529***
2004	2010	-.0848	2010	2015	-.5531***
2004	2011	-.2443	2010	2016	-.5158***
2004	2012	-.276*	2010	2017	-.4798***
2004	2013	-.3392**	2010	2018	-.4119***
2004	2014	-.2833*	2010	2019	-.4574***
2004	2015	-.3063**	2011	2014	-.5770***
2004	2016	-.3127**	2011	2015	-.5725***
2004	2017	-.3129**	2011	2016	-.523***
2004	2018	-.2817**	2011	2017	-.4805***
2004	2019	-.3248***	2011	2018	-.4042**
2005	2008	.0265	2011	2019	-.4556***
2005	2009	.0072	2012	2015	-.4384**
2005	2010	-.0956	2012	2016	-.4103**
2005	2011	-.2807	2012	2017	-.385**
2005	2012	-.3119*	2012	2018	-.3134*
2005	2013	-.3785**	2012	2019	-.3845**
2005	2014	-.3129**	2013	2016	-.3785*
2005	2015	-.3359**	2013	2017	-.3549*
2005	2016	-.3409**	2013	2018	-.2781
2005	2017	-.3384**	2013	2019	-.3631**
2005	2018	-.3037**	2014	2017	-.2528
2005	2019	-.3483***	2014	2018	-.182
2006	2009	.0914	2014	2019	-.2991
2006	2010	-.053	2015	2018	-.2632
2006	2011	-.2795	2015	2019	-.3826*
2006	2012	-.3151	2016	2019	-.3424
2006	2013	-.3907**			
2006	2014	-.3168*			
2006	2015	-.3426**			
2006	2016	-.3476**			