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- Microeconometric Evidence for Germany -

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Enrolment into Higher Education and Changes in Repayment Obligations of Student Aid
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Abstract: We evaluate the effect of the federal students' financial assistance scheme (BAfoeG) on enrolment rates into higher education by exploiting the exogenous variation introduced through a discrete shift in the repayment regulations. Supported students had to repay the full loan until 1990. Thereafter, 50 percent of the student aid has been offered as a non-repayable grant. Our results from simple difference-in-difference estimates suggest that student aid is ineffective in raising enrolment rates. Our findings may have important implications for the current debate on the reform of financing higher education in Germany and elsewhere.

JEL classification: I28, I22, J24
Keywords: educational decision, educational finance, higher education, difference-in-difference, discrete-choice

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1 Introduction

In Germany students from low-income families are eligible to financial aid under the federal students' financial assistance scheme (*Berufsausbildungsfoerderungsgesetz*, *BAfoeG*). This subsidy covers a substantial share of the monthly living costs of students enrolled at universities or technical colleges (*Fachhochschulen*). There are both efficiency and income distribution arguments justifying subsidies to higher education (see, e.g., Poterba 1996; Barr 2004). First, there may be positive external effects in the sense that social returns may exceed private returns to higher education. These may arise from progressive taxation and reduced welfare dependency of highly educated people, or spill-over effects from a highly educated and trained workforce to innovation and economic growth. Second, there may be too little investment into education of youth from low-income families. Governments may therefore want to provide subsidised loans or grants to students to foster 'equal opportunities' for otherwise disadvantaged youth.

These arguments also dominate the current discussion on the financing of higher education in Germany. In this paper, we evaluate the effect of BAfoeG on enrolment rates by exploiting an exogenous variation induced by a change in the BAfoeG repayment regulations in 1990. Before this reform, the full amount of financial aid obtained during university education had to be repaid (without interest) after graduation; since the reform only the half of this amount has to be repaid, the other half being offered as a non-repayable grant to eligible students. This implies that the debt burden of a fully supported student was on average reduced by some 23,500 DEM (12,000 EUR) from 47,000 DEM (24,000 EUR). Given this substantial subsidy, the reform was expected to induce more students from low-income families to enrol into higher education.

Using data from the German Socio Economic Panel (GSOEP) our estimation results from simple difference-in-difference estimations show that the 1990 BAfoeG reform seems to have been ineffective in raising enrolment rates into higher education. This somewhat surprising result may have important implications for the current policy debate on how to finance and secure access to higher education in Germany, and elsewhere.

The remainder of this paper proceeds as follows. In the next section we discuss the rationale for public subsidies to students and summarize empirical studies on the effects of student aid on enrolment decisions. In section 3, we present our empirical methodology to identify the effect of the mentioned policy change on enrolment rates into higher education in Germany. Estimation results are summarized and discussed in section 4, and section 5 concludes.

2 Theoretical Background and Previous Empirical Evidence

Following Becker (1962), economists usually analyze the decision to enrol into higher education in the framework of human capital theory.[1] According to standard human capital theory, an individual's education decision depends on the comparison between the discounted costs and future returns of an additional year of education. The higher the private costs of an additional year in educational is, the higher its private return in terms of future wages has to be to induce the individual to invest in education. In this simple model, higher direct costs of educational investment, such as tuition fees, would be associated with a lower optimal level of education and a higher private return to education. Likewise, lower financial educational net costs, by subsidised loans or grants to finance tuition fees and living expenses, would increase the optimal level of education and reduce its private return.

Under the assumption of perfect capital markets, the private return to education just equates its private marginal costs in a present value sense. Given time preferences, the optimum level of education is then defined by individual abilities or learning productivities. For a given ability level, individuals with a higher rate of time preference (individual discount rate) will choose a lower level of education, other things equal, and realise a higher return to education. Likewise, individuals who have to pay a higher rate of interest to finance their educational investment will choose a lower investment level. Given imperfect capital markets and/or a higher time preference prevailing among low-income households, the optimum level of investment in education would negatively depend on household income even if "ability" between students was controlled for. Of course, if imperfections in capital markets would not only result in different market interest rates but in binding credit constraints, this effect would be even stronger (Kodde and Ritzen 1985).

There are various distribution and allocation arguments for state intervention in the market for higher education (for summaries c.f. Hanushek (2002) and Poterba (1996)). One of the most important concerns the supposed existence of binding credit constraints for students from low income families. Not surprisingly, in this case state intervention can be rationalised not only by a distribution argument but also for reasons of economic efficiency. The efficiency argument is even stronger in case of external effects of higher education, i.e. if the social returns of higher education exceed its private return. In this case, higher enrolment rates into tertiary education may in fact lead to higher economic growth and social welfare.[2] Another important issue in education policy concerns the relative efficiency of loans and

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1 This literature is surveyed by Willis (1986) and Card (1999), among others.

2 For a summary of the theoretical and empirical literature on the relationship between private and social returns of education, as measured by its effect on economic growth see, e.g., Topel (1999).

grants subsidised or/and guaranteed by the state, and their financing in increasing enrolment rates in higher education (Barr and Crawford 1998; Barr 2003).

The positive correlation between enrolment rates and the level of parents' income found in several empirical studies for various countries has typically been interpreted as evidence for the existence of credit constraints in the market for student loans. This empirical correlation has been used to rationalise the provision of loans or grants along the lines mentioned above. This causal interpretation, however, is criticised on the basis of recent empirical research. Cameron and Heckman (1998) and Carneiro and Heckman (2002) show that the observed correlation between students' educational achievement and parental income can also be explained by a positive correlation between the latter and parental ability which itself is correlated with their children's ability. In another line of recent empirical research it has been shown that the potential effects of credit constraints may be very much mitigated if there is the option of some market work for students while enrolled at a college, and that the mentioned positive correlation can be explained by parental financial transfers which acts the same way as a reduction of tuition fees (Keane and Wolpin 2001; Keane 2002).

In contrast to this more structural estimation approach, recent empirical research on the effects of loans and grants on enrolment decisions into higher education simply relate this decision to variables suggested by basic human capital theory. These variables typically include financial indicators, such as parents' income, tuition fees, and student loans or grants. Most of these studies have been undertaken for the United States, while it seems that this topic has remained rather unexplored for Germany so far.[3]

As summarized by McPherson and Schapiro (1991), most US studies up to the beginning of the 1990s tend to find statistically and economically significant positive effects of financial factors on enrolment decisions. These studies also tend to find that the responsiveness of enrolment decisions is higher for students from low-income families. In McPherson and Schapiro's (1991) empirical investigation based on time series data on enrolment rates of three income groups between 1974 and 1984 finds that reducing the net-costs by 1,000 US-$, which is defined as the difference between tuition fees and the subsidy value of the student aid, would increase enrolment of low income students on average by about 6.8 percentage points, but would have an insignificant effect on enrolment rates of students from higher income groups. This is usually interpreted as evidence supporting the hypothesis of credit constraints in education choices.

3 There seem to be only very few empirical studies on this topic for other European countries, see Winter-Ebmer and Wirz (2002).

In a couple of recent related papers Dynarski analyzes the effect of various policy changes related to financial aid on students college enrolment decisions in the US. Dynarski (2002a) uses a difference-in-difference methodology on data frzm the Current Population Survey. The exogenous variation used to analyze college entry is the introduction of the Georgia HOPE scholarship which allows free attendance at the state's public colleges for residents with a certain minimum scholarly attainment in high school. The control group is composed of college freshmen in other south-eastern states. She finds that the introduction of the scholarship rose college attendance by 7.9 percentage points. Using the same methodology, Dynarski (2003) analyses the impact of the elimination of the US Social Security Student Benefit Program in 1982. The removal of this program affected youth entitled to student aid in case of the death of a parent during an individual's childhood. Dynarski (2003) finds that this policy change has increased enrolment rates by about 18 percentage points one average. This relatively large effect is, however, not comparable to the effect for the HOPE scholarship program because these programs affected different groups of people. In another paper also based on a difference-in-difference methodology, Dynarksi (2002b) uses as an 'natural experiment' the removal of home equity from the set of assets that are taken into account for the assessment in federal financial aid formula by the US Higher Education Amendment in 1992. Since home equity is a large proportion of US household net worth, this change was expected to have a strong impact on students' eligibility for financial aid and, hence, on enrolment decisions. Although, the effect of this policy shift on enrolment rates is insignificant in the full sample, she detects a significant positive effect in a sub-sample of homeowners, arguably the group of people most affected by the policy change.

In another frequently cited paper, Kane (1995) also applies a difference-in-difference methodology to evaluate the introduction of the Pell Grant program in the US, which is similar to the German BAfoeG by providing means tested financial support for student from low-income families. He compares the years around the introduction in 1973 and eligible students as the treatment group. According to his estimates, the introduction of the Pell Grant program had no effect on enrolment rates into higher education.

For Germany, the question how financial aid may effect enrolment decisions is rather unexplored. There seems to be only one econometric study that relates student aid to enrolment into higher education. Lauer (2000) includes some indicators for the provision of BAfoeG, derived from the German Socio Economic Panel (GSOEP), as explanatory variables in a discrete choice model. Her empirical results seem to show that increasing the study subsidy by 1,000 DEM (about 500 EUR) increases the enrolment rate by 0.8 percentage points on average. This relatively low estimate might be related to the other two BAfoeG indicator variables included as explanatory variables, namely BAfoeG entitlement and the loan share of the subsidy. Furthermore, her estimation results may be biased because of potential endogeneity of the BAfoeG indicator variables included in her enrolment equations.

3 Empirical Methodology

We use a large panel data set which allows us to identify for all youth who graduated from upper secondary education transitions into higher education and the eligibility to student aid according to the German federal financial assistance scheme. Since our panel data set spans the period 1984 to 2001 we can identify the effect of the change in the loan repayment obligation in 1990 which substituted 50 percent of the previously fully re-payable loan into a 50 percent grant on enrolment rates into higher education. We view this as a 'natural experiment' which allows us, using both the simple difference-in-difference method and discrete choice models estimated on panel data, to identify the causal effect of this policy change on enrolment rates into higher education in Germany. In the next subsection we provide some institutional background and, in particular, describe the 'natural experiment' in federal financial aid for students. After a brief description of our data and sample design we then discuss the identification and estimation of the effect of this policy change on enrolment rates into higher education in Germany.

3.1 The Reform of the BAfoeG Repayment Obligation as a "Natural Experiment"

To provide some background for the discussion of our empirical methodology applied to identify potential enrolment effects of changes in student aid, we start with a brief description of the German federal financial assistance scheme to promote education (*Bundesausbildungsfoerdungsgesetz,* BAfoeG). When introduced in 1971, this law was meant to allow all qualified young people to enter a university regardless of parent's financial capacity. BAfoeG has been changed many times since then and today subsidizes also pupils in secondary education, further education, and also youth enrolled in vocational training courses. The main political goal of BAfoeG remains, however, to encourage students from low-income families to study at universities or technical colleges.

The maximum amount of the subsidy is defined by the scheme and depends on whether the student attends a technical college or an university, whether the student lives with her parents, and how she is insured for health care. This so pre-defined maintenance need (*Bedarfssatz*) is compared to the financial capacities of the parents or in instances where the student is married by her spouse. The financial capacity takes various sources of income into account and is reduced by actual paid taxes, a lump sum for social security and considers also if an obligation exists to pay alimony for other persons. And finally, there is a basic allowance. Students are eligible for BAfoeG if the calculated maintenance need exceed the calculated financial capacities of the parents.

Initially, BAfoeG was usually provided in the form of a non-repayable grant to most eligible students, but in a few instances was granted as a loan. This was the case if the study subject was changed, or if the student had already completed an university degree and continued her study with another subject (*Zweitstudium*). The amounts for the maintenance needs and the basic allowances is to be adjusted every second year to keep pace with the cost of living.

In winter 1983/84, the first major BAfoeG reform changed the repayment regulations from a non-repayable grant to an interest-free loan that had to be paid back from future earnings. This change was associated with a marked reduction in enrolment rates of graduates from low income families, which dropped by some 18 percentage points from 81 percent to 63 percent between 1976 and 1986 (Beirat für Ausbildungsförderung 1988; table 26). On the basis of this observation the Advisory Board on BAfoeG (*Beirat für Ausbildungsförderung*) suggested to reform the repayment obligations and to split the financial aid into a 50 percent grant and a 50 percent loan. It was expected by the Board that such a substantial reduction of the BAfoeG debt burden would motivate students from low income families to increase their enrolment into tertiary education (Beirat für Ausbildungsförderung 1988; 111).

Following the suggestions of the Advisory Board, the 12th revision of BAfoeG reformed the repayment regulation in July 1990. From then onwards all supported students have had to pay back only 50 percent of the support from their future earnings. The eligibility criteria for BAfoeG remained by and large unchanged. Hence, this discrete change in the BAfoeG repayment regulations affected the net present value of the financial aid for those students who were eligible to BAfoeG. For a fully supported student, this changed repayment regulation meant on average a reduction of her debt burden from 47,000 DEM (24,000 EUR) to 23,500 DEM (12,000 EUR) (HIS 1987; 10).

3.2 Data and Sample Design

Our empirical analysis is based on the German Socio-Economic Panel Study (GSOEP). This is a longitudinal survey of individuals living in private households in Germany covering each year since 1984.[4] Since the BAfoeG repayment regulation was changed in 1990 (the year of

[4] We use all waves up to the year 2001. Since we obtain the income information from the calendar data, which refers to the previous calendar year, our observation period ends in 2000. Haisken-DeNew and Frick (2001)

unification of east and west Germany), we have to restrict our sample to west Germany. We also restrict the sample to people who have completed upper secondary schooling, since only these people are entitled to enrol into higher education at universities or technical colleges. We thus analyze, respectively, enrolment probabilities at these institutions and transition rates from upper secondary schooling into higher education observed within the period 1984 - 2000. In 2001, there was another change of the BAfoeG rules which made the subsidy more generous, but this will not affect our analysis since the observation period of our data ends before this change became effective. We distinguish between universities and technical colleges because students at these two institutions differ in terms of their upper secondary education, their future careers and the likely effect of their response to the change in BAfoeG rules.

Whether an individual is eligible to the study subsidy depends, as mentioned above, mainly on the financial capacity of the parents relative to the maintenance need of the individual student. However, whether an individual receives BAfoeG is only observed for students and not for those who decided not to enrol into tertiary education, even though these individuals might be eligible for BAfoeG. Potential eligibility has thus to be inferred from parents' income and other relevant information contained in GSOEP. We built thus a model to simulate BAfoeG eligibility for all individuals and for each year within the observation period. The simulation approach is briefly described in the appendix.

Our sample includes 735 school leavers with an entrance qualification for higher education. 133 are right-censored due to sample attrition or at the end of the observation period, and for 53 observation we could not calculate BAfoeG eligibility because of missing information on parents. If an individual has not enrolled into higher education within four years after the completion of upper secondary schooling she is defined as a 'non-student'. Sample attrition is handled in the estimation by treating these observations as right-censored at the time they are last observed in the sample, as described below. The construction of the sample and the exact coding of the basic variables are described in detail in the appendix.

Descriptive statistics for the remaining 561 observations are shown in table A1 in the appendix: 59 percent enrolled within four years after completing upper secondary schooling; 15 percent are observed to have enrolled at a technical college, 44 percent at an university. About 78 percent of our sample qualified for higher education by completing a gymnasium, i.e. 22 percent obtained this qualification from a specialised gymnasium. The enrolment

provide detailed information on the GSOEP data.

descision is taken by 66 percent after the BAföG repayment regulations were changed in 1990 and our simulation shows that 22 percent are eligible for the financial study support.[5]

Table A1 presents also descriptive statistics for the treatment and the control group, respectively. The income of parents of eligible students is on average only one third the income of parents of students not entitled to BAfoeG. The two groups also differ markedly in their parents' educational background. As regards enrolment rates into higher education, average rates differ between the two groups, while enrolment into a technical college does not differ between the treatment and the control group.

3.3 Identification and Estimation

We use the data and sample design as described to identify the effect of the change in the loan repayment obligation introduced by the BAfoeG reform in 1990 on students' enrolment decisions. We interpret this change as a 'natural experiment'. The discrete policy shift affected only the group of students entitled to the subsidy because of relatively low parental income. Ineligible students are not affected by the reform. This introduces an exogenous variation which we exploit to identify the effect of the reform. To do so, we employ a simple difference-in-difference estimator and several discrete choice models including appropriately defined dummy variables to account for the discrete policy shift. We also try to account for the potential presence of dynamic selection bias related to our sample design on the basis of a discrete-time hazard rate model.

Simple Difference-in-Difference Estimator

We use a difference-in-difference to examine the effects of BAfoeG eligibility on enrolment. A difference-in-difference estimation compares the enrolment decision of two groups (first difference): a treatment group – eligible students – and a comparison group that is not affected by the policy shift – ineligible students. This difference is then compared between the two time periods: before and after the discrete policy shift (second difference). Thus, the simple difference-in-difference estimator is:

[5] At the first glance, this might look like a small ratio. But we would like to stress that 79 percent of students did not receive BAfoeG between 1985 and 2001 (AG Hochschulforschung 2001; table 105a).

(1) $\alpha = \left[S\left(EB=1, D=1 \right) - S\left(EB=0, D=1 \right) \right] - \left[S\left(EB=1, D=0 \right) - S\left(EB=0, D=0 \right) \right],$

where $S(EB, D)$:= share of people enrolled at university
with (EB=1) / without (EB=0) BAfoeG eligibility,
after (D=1) / before (D=0) the reform.

The coefficient α measures the average effect of the reform on the enrolment share in the group of people affected by the reform, which is also known as the "average treatment effect on the treated" in the empirical policy evaluation literature (c.f. Meyer 1995; Blundell and Costa Dias 2000). The key identifying assumption is that the causal effect would be zero in the absence of the policy shift, i.e. any shift in the probability of enrolment of eligible students is attributable to the policy change.

The simple difference-in-difference estimator from equation (1) is equivalent to the α coefficient on the interaction term in the following simple pooled regression:

(2) $S_{it} = \alpha\left(EB \times D \right)_{it} + \beta EB_{it} + \gamma D_{it} + \varphi + \upsilon_{it}$,

where S_{it} is the schooling variable for person i in period t, EB and D are dummy variables as defined above, υ is an error term and α, β, γ and φ are parameters to be estimated. In order to yield unbiased estimates of the parameters in regression (2), the key identifying assumption mentioned above has to hold. This also implies that the expectation of the difference of the error terms after and before the policy change is the same for the two groups, i.e.: $E\left(\upsilon_{i1} - \upsilon_{i0} \mid EB = 1 \right) = E\left(\upsilon_{i1} - \upsilon_{i0} \mid EB = 0 \right)$.

Since S_{it} is a dichotomous dependent variable, a simple OLS regression (2) would obviously not be an appropriate estimation method. To take into account the inherent non-linearity of (2), we could estimate some non-linear function, such as simple binary logit model. This will be a special case of the discrete-choice models we now turn to.

Discrete-Choice Models

Econometric analyses of the decision to enrol into higher education using micro data are typically based on discrete-choice models ranging from simple static reduced-form binary logit models to dynamic structural models based on explicit inter-temporal optimisation (see in increasing order of sophistication

Manski and Wise (1983), Cameron and Heckman (1998), Keane and Wolpin (2001)). The basic idea underlying these models is that educational decisions are based on the comparison of utility levels associated with alternative choices, with the chosen education level determined by the highest obtainable utility level. In most empirical applications estimation is based on relatively simple reduced form models which relate the probability of enrolment into higher education to various financial variables, such as parental income, tuition fees, loans, grants, and a set of control variables.

McFadden (1974) shows that a discrete choice model derived from stochastic utility maximization can be represented by a multinomial logit (MNL) model. From a practical point of view, an important advantage of the MNL model is that it can easily be applied to decisions involving more than two alternatives. This is important for our analysis because, for the reasons given in section 3.2 above, we want to differentiate between enrolment into technical colleges and universities. One potential disadvantage of the MNL specification is that it implies the so-called 'independence from irrelevant alternatives' (IIA) assumption. That is, the relative log-odds-ratio between university and technical college does not depend on other alternatives similar to one of the included alternatives. In the estimation of the model we will test whether this assumption can be maintained.

Identification of the causal effect of the BAfoeG reform on individual enrolment decisions in the MNL model is the same as discussed above, and the estimated α coefficient still represents the average effect for those affected by the policy reform. We also control for covariates that potentially affect students' enrolment decisions into higher education, such as parental income and education, student's gender and age at graduation from secondary school. These control variables are captured by the vector **X**.

The probability of attaining a particular education level *j* for individual *i* in period *t* can be expressed by:

$$\text{(3)} \qquad \Pr\left(E_{it} = j\right) = \frac{1}{1 + \sum_{j=1}^{2} \exp\left(\alpha_j \left(EB \times D\right)_{it} + \beta_j EB_{it} + \gamma_j D_{it} + \delta_j \mathbf{X}_{it} + \varepsilon_j^m\right)}, \quad j = 0$$

$$\text{(4)} \qquad \Pr\left(E_{it} = j\right) = \frac{\exp\left(\alpha_j \left(EB \times D\right)_{it} + \beta_j EB_{it} + \gamma_j D_{it} + \delta_j \mathbf{X}_{it} + \varepsilon_j^m\right)}{1 + \sum_{j=1}^{2} \exp\left(\alpha_j \left(EB \times D\right)_{it} + \beta_j EB_{it} + \gamma_j D_{it} + \delta_j \mathbf{X}_{it} + \varepsilon_j^m\right)}, \quad j = 1, 2, \ldots J\ .$$

The coefficients in the base category – not enrolled (S = 0) – have been normalized to zero. Hence, equation (3) gives the probability of this alternative. If there are only two possible alternatives (j = 0,1), the MNL reduces to the binary logit model. For reasons of comparison, we will also estimate this model and test it against the more general specification with three alternative states.

The time-invariant individual effect ε_j accounts for unobserved heterogeneity and is assumed to come from an arbitrary discrete probability distribution with a small number of mass points, ε_j^m , with the following properties:

$$
\begin{aligned}
& E\left(\varepsilon_j\right)=\sum_{m=1}^{M} \Pr\left(\varepsilon_j^m\right)\varepsilon_j^m=0 \\
(5) \qquad & \sum_{m=1}^{M} \Pr\left(\varepsilon_j^m\right)=1 \\
& E\left(\varepsilon_j^m \mathbf{X}_{it}\right)=0,
\end{aligned}
$$

where the vector **X** contains not only the controls as above but also the group indicator variables and their interaction for the difference-in-difference; ε_j^m is assumed to be uncorrelated with all explanatory variables.

Instead of explaining educational attainment at a particular point in time one could also model transition rates between education levels. As stressed by Cameron and Heckman (1998), one important advantage of this alternative model specification is the possibility to account for dynamic selection bias in education decisions over time. Given that we only look at enrolments into higher education within a relatively short time period of 4 years, this potential modelling advantage may seem somewhat limited at first sight. However, taking into account the relatively large number of right-censoring in our data due to sample design and attrition, it turns out that accounting for this potential selection bias by modelling transitions between states to be important.

A further advantage of the MNL described above is that it can easily be re-stated in terms of a discrete-time hazard rate model (Steiner 2001). This allows us to account for sample attrition in a straightforward way, and also provides a more appealing interpretation of enrolment decisions in terms of transition rates into higher education. The observed variable statistically related to these transition rates is the duration between graduation from upper secondary school and enrolment into one of two possible states, j =1: technical college, 2: university. This duration is described by a non–negative random variable, T, which takes on integer values only. If an observation ends in the interval $[I_{t-1}, I_t]$, which will be one year in the empirical analysis, this variable takes on a value of $T = t$. The hazard rate for individual i, $\lambda_{ij}\left(t\right)$, is the conditional probability, of a transition into state j in year t. Given that no transition has occurred until the beginning of t the hazard rate is:

(6) $\lambda_{ij}\left(t \mid \mathbf{X}_{it}\right) = P\left[T_i = t, \Omega = j \mid T_i \geq t, \mathbf{X}_{it}, \varepsilon_j^m\right]$

with i = 1,2,...n; j = 1,2;

$\mathbf{X}_{it}$ = vector of covariates of individual i in interval t

Ω: = 1, if transition into technical college

= 2, if transition into university.

ε_j^m = time-invariant individual effect, with the above stated properties.

Assuming independence of transitions into the two states, conditional on the vector of covariates, the hazard rate into higher education is given by

(7) $\lambda\left(t \mid \mathbf{X}_{it}, \varepsilon_j^m\right) = \sum_{j=1}^{2} \lambda_j\left(t \mid \mathbf{X}_{it}, \varepsilon_j^m\right).$

In terms of the hazard rate, the probability of not having enrolled into higher education in period t, conditional on not having been enrolled up to period *t-1* is given by

(8) $P\left[T_k > t \mid T_k \geq t, \mathbf{X}_{it}, \varepsilon_j^m\right] = 1 - \lambda\left(t \mid \mathbf{X}_{it}, \varepsilon_j^m\right).$

The survivor function which gives the (unconditional) probability of not having enrolled into higher education up to period t, can be written as

(9) $P\left(T_k > t \mid \mathbf{X}_{it}, \varepsilon_j^m\right) = S\left(t \mid \mathbf{X}_{it}, \varepsilon_j^m\right) = \prod_{\tau=1}^{t-1}\left[1 - \lambda\left(\tau \mid \mathbf{X}_{it}, \varepsilon_j^m\right)\right].$

In terms of the respective hazard rate and the survivor function, the probability of a transition into state j in period t is given by

(10) $P\left(T_k = t, \Omega = j \mid \mathbf{X}_{it}, \varepsilon_j^m\right) = \lambda_j\left(t \mid \mathbf{X}_{it}, \varepsilon_j^m\right) \prod_{\tau=1}^{t-1}\left[1 - \lambda\left(\tau \mid \mathbf{X}_{it}, \varepsilon_j^m\right)\right].$

Assuming that, conditional on $\mathbf{X}_{\text{it}}$, all observations are independent, the sample likelihood function is given by

(11) $L = \prod_{i=1}^{n} \sum_{m=1}^{M} \Pr\left(\varepsilon_j^m\right) \prod_{j=1}^{2}\left[\lambda_{ij}\left(t_i \mid \mathbf{X}_{it}, \varepsilon_j^m\right)\right]^{\delta_{ij}} \prod_{\tau=1}^{t_i-1}\left[1 - \lambda_i\left(\tau \mid \mathbf{X}_{it}, \varepsilon_j^m\right)\right]$

with $\delta_{ij} = \begin{cases} 1, & \text{if individual } i \text{ makes educational transition } j \\ 0, & \text{otherwise.} \end{cases}$

Hence, for a person with an observed transition into higher education the contribution to the likelihood function is given by the respective transition probability in equation (10), for a censored spell it is given by the survivor function in equation (9), both written in terms of hazard rates. Note that the survivor function not only provides information for individuals right-censored at the end of the observation period, but also for those who left the panel due to sample attrition.

It remains to specify a functional form for the hazard rate, which is formally equivalent to the MNL specification, i.e.:

$$\text{(12)} \quad \lambda_{ij}\left(t \mid \mathbf{X}_{it}\right) = \frac{\exp\left(\alpha_j \left(EB \times D\right)_{it} + \beta_j EB_{it} + \gamma_j D_{it} + \delta_j \mathbf{X}_{it} + \varepsilon_j^m\right)}{1 + \sum_{j=1}^{2} \exp\left(\alpha_j \left(EB \times D\right)_{it} + \beta_j EB_{it} + \gamma_j D_{it} + \delta_j \mathbf{X}_{it} + \varepsilon_j^m\right)}, \quad j = 1, 2.$$

where the vector $\mathbf{X}_{it}$ also includes three dummy variables (with the first year dummy as the base category) to account for duration effects on the hazard rate. The random effect is assumed to share the same properties as above. Note that the explanatory variables in (12) are allowed to vary of time, which provides an additional source of information for the estimation of the model.

Plugging the hazard rate (12) into the likelihood function (11), ML estimates of the parameters, the mass points and their probabilities, taking into account the above mentioned restrictions on the individual effects, can be obtained by standard numerical optimization procedures.[6]

4 Estimation Results

We first present simple difference-in-difference estimates by calculating the means of enrolment rates of the treatment and the control group, before and after the repayment regulations were changed. Using simple linear regression analysis we show that the results from simple difference-in-difference estimates may depend on the sample design. Then we present estimation results from a binary logit model, which is a more appropriate specification for the binary outcome variable, where we also control for other potential determinants of individual enrolment rates. The binary logit model is a special case of the discrete choice models described in section 3.3 above. Since enrolment decisions may differ between technical colleges and universities due to eligibility criteria, expected careers as well as future earnings, we also estimate multinomial logit models as described in section 3.3 and test for these potential differences. Finally, instead of enrolment probabilities we model transition rates into higher education on the basis of the discrete-time hazard rate model also described in the previous subsection, which allows us to account for dynamic selection bias related to sample attrition.

[6] The *gllamm* programme as implemented in Stata 8 is used for the estimation. For a description and technical details see Rabe-Hesketh, Skrondal and Pickles (2001).

4.1 Simple Difference-in-Difference Estimates

Given the validity of the identifying assumptions mentioned in the previous section, it is straightforward to calculate the simple difference-in-difference estimator of the effect of the BAfoeG reform on the average enrolment rate of eligible students from Table 2. The table shows average enrolment rates for four groups: the treatment group of low income youth eligible to BAfoeG and the control group of non-eligible youth, both after and before the policy reform. The third column shows the first differences. Enrolment rates of eligible students rose by 28.8 percentage points, while enrolment of the control group increased by only 21.3 percentage points. As shown in the table, the difference-in-difference in mean enrolment rates amounts to 7.6 percentage points, which is the average treatment effect for those affected by the BAfoeG reform.

Table 2: Difference in difference of means

	after	before	difference
eligible for BAfoeG	0.840	0.552	0.288
ineligible for BAfoeG	0.644	0.431	0.213
difference-in-difference			*0.076*

Note: Means of the school leaver cohorts 1984-1986 and 1990-1992.

This treatment effect can also be obtained from a linear probability model estimated on individual data as given by equation (2) in the previous section. Since estimated standard errors from OLS regressions are known to be biased due to heteroscedasticity, we calculate adjusted standard errors based on the estimated variances of the errors. The first two columns of Table 3 report WLS estimation results for the selected sample of school leavers in two periods of equal length before and after the policy change, which corresponds to the sample used for the simple difference-in-difference estimate derived above. Hence, the coefficient on the interaction between the group dummy and the time dummy in column (1) of Table 3 is numerically identical to the difference-in-difference estimate in table 2. However, as the estimated standard error of the coefficient estimate in Table 3 shows, the estimated treatment effect is not statistically significantly different from zero.

Estimation results in column (2) of Table 3 refer to the full sample of freshmen. Thus, we do not restrict the observation period to be of equal length before and after the policy change. This increases the sample size substantially and may also avoid some potential selectivity effects associated with the sample selection in the previous estimation. Estimation results in column (2) show that the estimated coefficient on the relevant interaction term is markedly reduced in size and also remains statistically insignificant.

Table 3: Enrolment probability in higher education

	Linear Probability Models		Logit Model	
	(1)	(2)	(3)	(4)
constant	0.431 (0.048)**	0.597 (0.041)**	0.394 (0.170)*	-8.984 (1.815)**
after	0.212 (0.071)**	-0.057 (0.050)	-0.231 (0.206)	-0.130 (0.225)
eligible for BAfoeG	0.120 (0.103)	0.107 (0.080)	0.475 (0.372)	0.712 (0.413)+
after × eligible for BAfoeG	0.076 (0.143)	0.040 (0.100)	0.155 (0.461)	0.266 (0.504)
father self-employed	–	–	–	0.499 (0.352)
father white collar	–	–	–	0.250 (0.250)
father civil servant	–	–	–	0.750 (0.318)*
father out of labour force	–	–	–	-0.460 (0.506)
male	–	–	–	0.217 (0.192)
abitur	–	–	–	1.188 (0.233)**
school leaving age	–	–	–	0.400 (0.091)**
father completed upper secondary schooling	–	–	–	0.467 (0.259)+
mother completed upper secondary schooling	–	–	–	-0.050 (0.335)
R^2	0.08	0.02	–	–
log-likelihood	–	–	-375.75	-335.63
χ^2	–	–	8.65	88.88
observations	243	561	561	561

Notes:

a) Estimation results in column (1) refer to a selected sample of school leavers in two periods of equal length before and after the BafoeG reform, i.e. school leaver cohorts 1984-1986 and 1990-1992.
b) Estimation of the linear probability model in columns (1) and (2) is based on Weighted Least Squares to account for heteroscedasticity.
c) Standard errors are in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%.
d) The base category for father's occupational status is blue-collar worker.

4.2 Binary Logit Estimates

To account for the inherent non-linearity of the dichotomous dependent variable, in columns (3) and (4) of Table 3 we present logit estimates for the simple model and for the model with addition control variables. Estimation of this model is based on all observations within the observation period and should therefore be compared to estimation results in column (2). As expected, the WLS and logit coefficient estimates in columns (2) and (3) are virtually identical after normalization. Other things equal, enrolment rates are higher if the father has completed upper secondary schooling, if students obtained their entrance qualification for a higher education institution by a degree from a general gymnasium rather than a specialised gymnasium, and the higher the school leaving age. However, controlling for these covariates does not change the insignificance of the estimated treatment effect.[7]

We have also tested for homogeneity of coefficients of explanatory variables for the treatment and the control group. Although the null hypothesis of equality of coefficients was rejected for almost all explanatory variables, allowing the coefficient of these variables to differ between the two groups has essentially no effect on the estimated treatment effect.

4.3 Multinomial Logit Estimates

In table 4 we summarize estimation results for the MNL model with enrolment at a technical college or at an university as alternative choices of higher education. Coefficients are to be interpreted relative to the base category, which is not being enrolled at either of the two mentioned alternatives. Note, however, that the marginal effect of a MNL model depends not only on the estimated coefficient but also on all other estimated coefficients which may affect both the size and the sign of the effect (Greene 2003; 722).

Estimation results for model (1) show that the effect of a change in the BAfoeG repayment regulation is insignificant for both choices. This holds true regardless whether or not we include other control variables, as in model (2). Only a few of these variables are significant: Males have a higher probability to register with a technical college and having a father, who completed upper secondary schooling, raises the probability to enter an university, whereas having obtained a degree from a general gymnasium only affects enrolment into university but not into a technical college.

Finally we have tested the validity of the independence of irrelevant alternative (IIA) assumption underlying models (1) and (2). The IIA assumption can be tested by introducing an additional alternative which is similar to one of the already included choices. A potential relevant alternative could be to pursue vocational training after completing upper secondary schooling. Büchel and Bausch (1998) argue that risk averse students might pursue vocational training before or instead of enrolment into higher education. On the basis of a Hausman specification test (Hausman and McFadden 1984) we cannot reject the null hypothesis that the IIA assumption is not violated.

[7] A test on the joint significance of parents' income and its square shows that parent's income has no significant effect on enrolment rates (χ^2=0.97 with 2 degrees of freedom). We thus disregard these variables in our analysis.

Table 4: Enrolment probability in technical college or university – multinomial logit estimates

	(1)		(2)		(3)	
	technical college	university	technical college	university	technical college	university
after	-0.159 (0.305)	-0.258 (0.221)	-0.031 (0.319)	-0.187 (0.248)	-0.305 (0.568)	-0.513 (0.594)
eligible for BAfoeG	-0.209 (0.624)	0.632 (0.383)+	-0.048 (0.657)	0.978 (0.451)*	1.553 (1.284)	3.265 (1.320)*
after × eligible for BAfoeG	0.799 (0.730)	0.012 (0.480)	0.813 (0.769)	0.081 (0.551)	1.008 (1.354)	0.065 (1.442)
father self-employed	–	–	0.766 (0.476)	0.389 (0.391)	1.406 (0.835)+	1.353 (0.854)
father white collar	–	–	0.392 (0.357)	0.185 (0.280)	0.781 (0.575)	0.778 (0.580)
father civil servant	–	–	0.627 (0.470)	0.779 (0.348)*	1.621 (0.888)+	2.090 (0.923)*
father out of labour force	–	–	0.340 (0.668)	-0.913 (0.611)	-0.050 (0.995)	-1.757 (1.051)+
male	–	–	0.896 (0.297)**	-0.042 (0.211)	1.493 (0.547)**	0.614 (0.555)
abitur	–	–	-0.288 (0.282)	2.584 (0.383)**	0.942 (0.540)+	4.386 (0.719)**
school leaving age	–	–	0.335 (0.113)**	0.419 (0.110)**	0.791 (0.225)**	1.222 (0.275)**
father completed upper secondary schooling	–	–	0.227 (0.381)	0.544 (0.278)+	0.470 (0.749)	0.751 (0.746)
mother completed upper secondary schooling	–	–	-0.616 (0.570)	0.119 (0.358)	-1.150 (0.923)	-0.371 (0.881)
constant	-0.969 (0.250)**	0.098 (0.181)	-8.386 (2.243)**	-10.813 (2.236)**	-19.035 (4.850)**	-33.026 (126.680)
mass points:						
ε_1	–	–	–	–	-4.528 (1.371)**	-16.34 (373.968)
ε_2	–	–	–	–	1.538	5.551
prob(ε_1)	–	–	–	–	0.254 (0.043)**	
prob(ε_2)	–	–	–	–	0.746	
Observations	561		561		561	
log-likelihood	-561.28		-478.60		-469.81	
χ^2	11.99		177.35		17.58	

Notes:
a) Standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%.
b) Base category: staying out of tertiary education.
c) The χ^2 statistic of column (3) compares the log-likelihood of model (3) versus model (2).
d) ε_1 and its probability is estimated. ε_2 is calculated according to the properties mentioned in the text.

The last two columns show the estimation results of model (3) where individual random effects account for unobserved heterogeneity. Including two mass points for each category improves the log-likelihood significantly suggesting that unobserved heterogeneity effects are present in our data. Taking these unobserved effects into account, however, does not alter the insignificance of the average treatment effects, neither for the choice to enrol into a technical college nor for the choice to enrol into an university.

4.4 Estimation Results for Transition Rates

Multinomial logit estimates for transition rates into higher education are presented in table 5. As in the previous subsection, we present results for the base model (1), for model (2) with additional control variables, and for the random effects specification (3). These models differ from the MNL in the previous section in that, instead of explaining the enrolment at a technical college or an university at a particular point in time, they explain the respective transitions into higher education within a period of four years (in the uncensored case). In addition to the control variables also included in the MNL models of the previous subsection, the transition models also include baseline hazard dummies to account for the effect of process time ("duration dependence") on enrolment rates.

The estimated treatment effect is insignificant for both the transition rate into a technical college and into university in all specifications. However, the sign of the treatment effect turns negative for enrolment into a technical college but remains highly insignificant.

Another interesting result in table 5 concerns duration effects on transition rates into higher education. The estimation results show that transition rates are decreasing over time, that is students are less likely to pursue higher education if they have not enrolled right after having completed higher secondary schooling. However, this duration effect is only significant for the transition rate into university, whereas the baseline dummies are neither individually nor jointly significant in the transition rate into a technical college. Including control variables does not change these patterns. Enrolment rates into university still depend negatively on duration, whereas we could not find any duration effects for enrolment into a technical college.

The last tow columns show the estimation results of model (3) where individual random effects account for unobserved heterogeneity in transition rates. Including two mass points for each category improves the log-likelihood significantly suggesting that unobserved heterogeneity effects are present. Taking these unobserved effects into account, however, does not alter the insignificance of the average treatment effects, neither for the transition into a technical college nor for the transition into an university.

Table 5: Enrolment rates into technical college or university

	(1)		(2)		(3)	
	technical college	university	technical college	university	technical college	university
year 2	0.328 (0.271)	0.117 (0.157)	0.360 (0.266)	0.212 (0.163)	0.303 (0.294)	0.835 (0.241)**
year 3	0.084 (0.316)	-0.628 (0.220)**	0.175 (0.321)	-0.494 (0.230)*	0.046 (0.346)	0.522 (0.363)
year 4	-0.133 (0.371)	-1.175 (0.296)**	-0.044 (0.383)	-1.014 (0.304)**	-0.177 (0.408)	0.250 (0.506)
after	0.511 (0.269)+	0.346 (0.162)*	0.686 (0.274)*	0.404 (0.172)*	0.745 (0.317)*	0.595 (0.254)**
eligible for BAfoeG	0.236 (0.364)	-0.206 (0.230)	0.484 (0.364)	0.006 (0.243)	0.591 (0.420)	0.013 (0.339)
after × eligible for BAfoeG	-0.542 (0.523)	0.194 (0.310)	-0.695 (0.521)	0.146 (0.336)	-0.897 (0.589)	0.056 (0.462)
father self-employed	–	–	0.503 (0.400)	-0.007 (0.283)	0.641 (0.445)	-0.357 (0.492)
father white collar	–	–	0.143 (0.291)	-0.063 (0.210)	0.287 (0.339)	-0.529 (0.330)
father civil servant	–	–	0.314 (0.403)	0.350 (0.245)	0.484 (0.450)	0.132 (0.398)
father out of labour force	–	–	0.118 (0.665)	-0.902 (0.530)+	0.603 (0.851)	-2.051 (0.713)**
male	–	–	0.883 (0.265)**	-0.157 (0.149)	1.072 (0.309)**	-0.769 (0.278)**
abitur	–	–	-0.675 (0.237)**	2.249 (0.339)**	-1.230 (0.482)*	3.421 (0.477)**
school leaving age	–	–	0.343 (0.093)**	0.324 (0.084)**	0.288 (0.106)**	0.734 (0.132)**
father completed upper secondary schooling	–	–	0.147 (0.317)	0.366 (0.185)*	0.206 (0.363)	0.357 (0.309)
mother completed upper secondary schooling	–	–	-0.372 (0.490)	0.062 (0.247)	-0.499 (0.554)	0.460 (0.414)
constant	-3.096 (0.258)**	-1.613 (0.140)**	-10.329 (1.862)**	-10.130 (1.607)**	-9.751 (2.136)**	-20.152 (2.889)**
mass points:						
ε_1	–	–	–	–	1.226 (1.055)	-2.825 (0.738)**
ε_2	–	–	–	–	-0.875	2.017
prob(ε_1)	–	–	–	–	0.416 (0.265)+	
prob(ε_2)	–	–	–	–	0.584	
Observations	1630		1630		1630	
Log-likelihood	-998.38		-913.44		-903.67	
χ^2	37.60		172.90		19.54	

Notes: see table 3.

5 Summary and Conclusion

We have analysed the effect of a discrete policy shift in federal student aid in Germany introduced by the BAfoeG reform in 1990 on enrolment rates into higher education. In 1990, the repayment regulations were changed with the expectation that enrolment rates would raise, and that more young people originating from low-income families would pursue tertiary education. Before the reform, the full loan became due after graduation. The reform reduced the debt burden of student aid by 50 percent, the other half was transformed into a non-repayable grant. We interpret this as a 'natural experiment' and exploit this supposedly exogenous variation to identify the causal effect of more generous student aid on enrolment rates into higher education.

Estimation results from both simple difference-in-difference estimates and discrete-choice on the basis of data from the German Socio Economic Panel (GSOEP) spanning the years 1984 – 2000 show that this substantial reduction of the debt burden was ineffective in raising enrolment rates. This somewhat surprising result is robust to various model specifications. One possible explanation for the insignificant effects of the BAfoeG reform on enrolment rates is that our basic identifying assumption of a common time trend for the treatment and control groups is violated. We cannot test this hypothesis, of course, nor can we rule out this possibility on a priori grounds. For example, it could be possible that the decline in the private returns to education documented for Germany in Boockmann and Steiner (2000) and Lauer and Steiner (2001) has had different effects on enrolment decisions of youth from low-income households and those not entitled to BAfoeG. Although this may seem theoretically plausible because youth from low-income households may, due to credit constraints and/or a higher rate of time preference, request a higher private return to education to induce them to enrol into higher education, there seems to be no evidence supporting this view. Hence, for the time being, we interpret our empirical results as indicative for the ineffectiveness of more generous student aid in raising enrolment rates into higher education in Germany.

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Appendix

Construction of Sample used for Estimation from the GSOEP

Our analysis is based on the German Socio-Economic Panel Study (GSOEP), which is a longitudinal survey of individuals living in private households. Since GSOEP targets households and does not directly focus on the transition between secondary and tertiary education, we have to derive this information from the following questions. The second wave of GSOEP asks in question 53:

"Since the beginning of 1984 have you finished school, vocational training, or university?",

and proceeds with the question:

"What type of qualification did you get?"

This information defines who has obtained a specialised upper secondary school degree (*Fachhochschulreife*) or a upper secondary school degree (*Abitur*) and is thus qualified to enrol into higher education. This question is also asked in the proceeding waves in the GSOEP from which each person's school leaving year can be derived.

Interviewees are also asked what they are currently doing in each year. For students, we can thus derive the enrolment year from the questions:

"Are you currently in training, attending school, undergoing vocational training or attending a further training course?",

and if yes:

"What sort of training is it?".

If it is either a technical college (*Fachhochschule*) or university, we know the year and institution of enrolment.

We allow the student to defer the enrolment decision up to four years. If a student does not attend higher education within four years, she is classified as a non-student. The deference period is justified because males have to do their military duties which takes between 10 and 18 month conditional on the recruitment year; some students decide to engage in vocational training before they enrol, which takes between 2,5 and 3,5 years; and finally is enrolment conditioned on waiting terms (*Wartesemester*) for some courses, due to the central study place allocation agency (*Zentrale Studienplatzvergabe, ZVS*).

Simulation of BAfoeG Eligibility

Whether an individual receives financial support through BAfoeG or not is only observed for students enrolled into higher education. But since BAfoeG is means tested, some individuals would be eligible if they enrolled into higher education. Since this counterfactual BAfoeG eligibility is not observable, we apply a small micro simulation model to infer who is eligible for the financial study support and who is not. In this appendix, we briefly describe our micro simulation model.

The BAfoeG regulations define the maintenance needs for students conditional on the student's living situation, i.e. whether she lives with her parents or on her own. Subtracted from these maintenance needs are the financial capacities of the student, her husband, and her parents. Since the financial capacity of the parents has the major influence on eligibility, we abstract from own and husband/wife's income.

The relevant income to define parents' financial capacity is post-tax labour, asset and pension earnings from the father and the mother. Income tax and social security liabilities are only available for the household and not for the individuals. We depart thus from the individual level and calculate the relevant income on the household level. If parent do live together, this is straight forward. If they, however, do not share the same household, we take net-tax income from the father's and the mother's household separately. If the father or the mother shares the household with another spouse, we take the half of net-tax household income. An allowance is granted on parents' income conditional on the family status and for each child that is entitled for alimony. A share of the remaining income – that again depends on the amount of alimony entitled children – is then subtracted from the maintenance needs. If the difference is positive the individual is eligible ($BE_t=1$) for the study support and vice versa. The two equations may clarify the simulation idea.

(A1)

$$\begin{aligned} BAfoeG_t = & \left(\text{maintenance needs} \middle| \text{living status}\right)_t \\ & -\left[\left(\text{parents' income}\right)_t - \left\{\left(\text{allowance}_1 \middle| \text{family status}\right)_t + \left(\text{allowance}_2 \times \text{children}\right)_t\right\}\right] \\ & \times\left(1-\left[\text{allowance}_3 + \text{allowance}_4 \times \text{children}\right]_t\right) \end{aligned}$$

(A2) $$BE_t = \begin{cases} 1 \text{ if } BafoeG_t > 0 \\ 0 \text{ if } BafoeG_t \leq 0 \end{cases}$$

The simulations routine runs for each individual over all observed periods, i.e. from 1984 till 2000.

Table A1: Descriptive Statistics

Variable	Full sample	Eligible for BafoeG (treatment group)	Ineligible for BafoeG (control group)
higher education	0.588	0.694	0.559
technical college	0.150	0.149	0.150
university	0.439	0.546	0.409
after	0.665	0.636	0.673
eligible for BAfoeG	0.216	1.000	0.000
father self-employed(b)	0.098	0.091	0.100
father white collar(b)	0.342	0.174	0.389
father civil servant(b)	0.196	0.099	0.223
father out of labour force(b)	0.037	0.083	0.025
male	0.558	0.479	0.580
abitur	0.777	0.777	0.777
father completed upper secondary schooling	0.267	0.099	0.314
mother completed upper secondary schooling	0.103	0.033	0.123
parents' income/1,000	6.222 (3.612)	2.795 (1.436)	7.164 (3.458)
school leaving age	19.615 (1.114)	19.810 (1.240)	19.561 (1.072)
observations	561	121	440

Notes: (a) Standard errors, where applicable, are in parenthesis.
(b) Dummy base for father's occupational status is blue collar.