Why Do German Students Reject Free Money?

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Abstract

A significant number of German students do not apply for student aid (BAföG) despite eligibility. We build a simple theoretical model to show how the combination of imperfect information, risk aversion, debt aversion, and student income can incentivize rational students to abstain from an application for aid. We use GSOEP data from 2001 - 2013 to simulate BAföG eligibility and show that in particular risk averse students with low income are discouraged if they do not receive additional information about the application procedure. Moreover, debt-averse students are more reluctant to apply for aid. Our results suggest that a non-transparent and complicated student aid system disproportionally discourages poor students with little experience with the BAföG system.

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1 Introduction

Tuition fees at German federal institutions of higher education are virtually non-existent, and only small administration fees have to be paid by students. What remains to be covered are expenses for basic needs and accommodation. Among several options to finance living expenses, students can receive financial help from their parents, work to earn their own income, or apply for scholarships and student federal aid, also known as *BAföG*, which is provided by the Federal Training Assistance Act (*Bundesausbildungsförderungsgesetz*). Depending on various socioeconomic factors, students can receive monthly BAföG payments for the nominal length of their studies. Half of the total BAföG aid is a grant that never has to be paid back and the other half is an interest-free loan with the repayment being capped at 10,000 EUR (Bundesministerium für Bildung und Forschung, 2017). According to the latest student survey *21. Sozialerhebung* published by the Federal Ministry of Education and Research, approximately 79% of students who receive BAföG state that without federal aid they would have not been able to study (Middendorff et al., 2017).

In 2012, approximately 67% of students were formally eligible to receive BAföG, i.e., they met the prerequisite to be still under 30 years old when starting their first full-time study program (Herber and Kalinowski, 2016). Out of these formally eligible students, only 28% received BAföG (Deutscher Bundestag, 2014). There are two potential explanations behind the low share of recipients: Either the students fail the means test for student aid, or they choose to not apply for aid even though they are eligible for a positive aid amount. While the former explanation is in line with the purpose of the BAföG system, the latter would mean that it fails to support students that are targeted by the system.

The previously mentioned student survey *Sozialerhebung* provides some insights why some of the students did not file a BAföG application form in the first place. As the top runner, 76% of students state that according to their own expectations, either their parents' or partner's income was too high, followed by 30% of students saying that their own income was too high. Remarkably, 25% of all students state that they did not apply due to the fact that they did not want to accumulate debt. When only students from lower educational backgrounds are considered, the share of students who state that making debt was the main reason for non-application increases to 37% (Middendorff et al., 2017).

This paper shows how the combination of information frictions, attitude towards risk, student income and debt aversion can rationalize this behavior. A student who is eligible for aid but does not apply forgoes financial resources, considering that in the German student aid system, half of the payment is a free subsidy to the student and the other half is a zero interest loan. Essentially, not applying for BAföG directly translates into rejecting free money. This is particularly controversial for students in Germany, since upward mobility for German students to tertiary education is still very low compared to other OECD countries (OECD, 2016; Herber and Kalinowski, 2016). Germany has a low participation rate in higher education and also the lowest growth rate in tertiary education in Europe, which Powell and Solga (2011) call "German exceptionalism". Student aid is also supposed to increase enrollment rates to higher education institutions (Cornwell et al., 2006; John and Noell, 1989) and encourage potential students to enroll earlier to universities (Steiner and Wrohlich, 2012). Moreover, financial aid can also raise the probability that a student finishes her studies successfully instead of dropping out early (Glocker, 2011).

We first set up a theoretical model that illustrates the rational decision of a student whether to apply for BAföG. In the presence of imperfect information about the entitled amount of aid, risk aversion, debt aversion, and a costly application process, a student might find it optimal to refrain from applying for aid. The model shows that stronger information frictions give rise to a higher likelihood for non-application. While in general, poorer students are more likely to apply for aid, they are also more affected by these information frictions. Moreover, the more risk averse a student is, the higher the likelihood to turn down the application. A student with higher risk aversion reacts also more severely to any changes in the information level as well as changes in student income. Lastly, a high degree of debt aversion deters students from applying for BAföG, irrespective of all other factors.

These hypotheses are tested using panel data provided by the GSOEP (German Socio-Economic Panel), in which students during the years $2001 - 2013$ are observed. Since the SOEP does not include information on students' eligibility for BAföG, we simulate for each student potential BAföG amounts. We only keep eligible students in the sample, which then reduces the number to $N = 988$ observations or $n = 412$ students over 13 years. We first use a pooled probit model to predict the probability to not receive BAföG conditional on being eligible. We then control for unobserved heterogeneity with a random effects (RE) probit and correlated random effects (CRE) probit model and find evidence for unobserved heterogeneity. The RE probit shows that an increase of the monthly parental gross labor income by 1% increases the probability to not apply for BAföG despite eligibility by remarkable 40% (significant at 0.1%-level). This suggests that the misconceptions about

eligibility increase with parental income. An increase of student's age by 1 year increases the probability to reject BAföG by 3.3% at a 0.1% significance level in the pooled probit. Thus, older students mistakenly assume to not be eligible, as they are not well informed enough about the actual age limit. A three-way interaction testing for the relationship between risk aversion, income and information level is highly significant at a 0.1% significance level.
Students with high risk aversion and strong information frictions (no siblings receiving BAföG or being an only child) are particularly likely to not apply for aid. Additional information via a sibling receiving BAföG reduces the non-take-up rate, with stronger effects for poorer students. Students with low risk-aversion are more likely to apply for student aid in general, while the level of information has a very moderate effect. Moreover, we find that if a student is more accustomed to debt because her family is paying back monthly credit rates, the probability to reject BAföG decreases by 6.9% at a 10% significance level in the pooled probit. This suggests that debt averse students are more likely to refrain from an application for aid.

The remainder of the paper is structured as follows: Chapter 2 provides some background information about the BAföG system and reviews the most relevant literature. In chapter 3, we build a simple theoretical model to illustrate the student's application decision and derive several testable hypotheses. Chapter 4 tests these hypotheses using GSOEP data and discusses the empirical results. The 5th chapter concludes.

2 Literature Review and Background Information

2.1 Financing Studies in Germany

The *Sozialerhebung* reports that the average disposable income of a student was 918 EUR per month in 2016, where the most important income source was financial help from parents and student's own labor income. Only 1/4 of all students received BAföG with an average amount of 435 EUR per month. Other minor income sources were savings, financial help from relatives and partners, scholarships and student loans such as the KfW credit (Middendorff et al., 2017).

When introduced in 1970, BAföG was a 100% grant for students and about 45% of all students were receiving it. Since then, the system has been adjusted and reformed multiple times. In 1979, the age limit was decreased from 35 to 30 (Deutscher Gewerkschaftsbund, 2016). Starting in 1982, students could only receive an interest-free loan as aid, while in 1991, BAföG has been modified to a grant-loan aid. In the past decades, the share of students who have been supported by BAföG has decreased over time. Nowadays, the downward trend of eligibility for aid is still ongoing and the government tries to cope with this problem by increasing income set-offs and maximum aid entitlements. A more recent reform in 2001 addressed the repayment of BAföG and capped the total amount of debt at 10,000 EUR. Moreover, child allowances by the government, which are paid to German students until they are 25 years old, were not considered as student income anymore. With the next reform in 2008, so called mini-jobs[1], which are fairly prominent among German students, were not affecting aid entitlements anymore. In 2010, another reform increased entitlements by 2% and rose the age limit for Master students from originally 30 to now 35 years (Deutsches Studentenwerk, 2017).

In the 21$^{\text{th}}$ BAföG report the federal government states that the total number of students has increased between 2012 and 2016 by 15% (from 2,358,000 to 2,709,000). Also, the share of formally eligible students increased by 9% (from 1,572,000 to 1,709,000). However, the number of aid-receiving students has decreased by 14.3% (from 440,000 to 377,000). This clearly shows that while the number of formally eligible students increased, the share of students who actually receive aid in the long-run could not be stabilized (Deutscher Bundestag, 2017).

2.2 Literature

Federal student aid via BAföG is a specific type of governmental aid and its implementation might be subject to barriers that are similar to other public aid measures. Bruckmeier et al. (2013) analyze a sample survey of income and expenditure in 2008 and find that approximately $34-43\%$ of all the people who are eligible for unemployed benefits (*Arbeitslosengeld II*) in Germany do not apply for public assistance. This reluctance to take up benefits is driven by high information costs, bureaucratically complex forms and stigma effects. The revelation of the unemployment status to other people by going to the job center or the general negative perception of being unemployed is considered to be painful and ashaming. Kayser and Frick (2000) analyze social assistance (*Sozialhilfe*) for German households via the GSOEP in 1996 and find that the non-take-up rate[2] accounts to

[1] Mini-jobs are jobs in which individuals can earn up to 450 EUR monthly without having to pay income taxes.

[2] The non-take-up rate shows the percentage of people not applying for aid conditional on being eligible for aid.

63.1%, whereas stigma, application cost and social ties affect the decision of a(n) (non-)application. However, there is no evidence that such a stigma is attached to receiving student aid.

There is growing evidence that information frictions, application costs and bureaucratically complex forms can prevent students from applying for aid. Bettinger et al. (2012) consider the complexity of the Free Application for Student Federal Aid (FAFSA), which students need to complete in order to apply for several federal aid programs in the US. They show that assisting students through the application process and providing more information about the program increases the likelihood of FAFSA completions as well as the likelihood to attend college, persevere until graduation, and receive aid. Dynarski and Scott-Clayton (2006) refer to the complexity of the FAFSA by focusing on compliance costs, which "include the time and resources required to learn about the system and its rules, collect all of the required documents, and fill out the form". They find that compliance costs are higher for those students who come from low-income families, which counteracts the goal of helping especially students with limited financial support. In contrast, Booij et al. (2012) analyze information restrictions related to Dutch student loans and contrary to their expectations, they cannot show that informing students about loan conditions gives rise to higher participation rates. The filing process for the German BAföG is generally perceived to be too complex by itself, intimidating students and posing an additional hurdle for the application. First-time applicants need on average 335 minutes to fill out the BAföG form, whereas the time needed to fill out a continuation form decreases to 261 minutes (Bundeskanzleramt und Nationaler Normenontrollrat, 2010).

Some students might worry about the non-completion of their studies and hence, the risk of not having a sufficiently high income in order to be able to pay back the loan part of BAföG. Approximately 28% of Bachelor students in Germany drop out of higher education and do not receive their degree, whereas for Master students the share equals to 11% (Heublein et al., 2014). Ortiz-Nuñez (2014) finds that a student's willingness to take financial risk increases the probability to take out a student loan. He further emphasizes that there is a shortage of literature in this framework as it might be difficult to find "a suitable measure of risk attitudes". Monge-Naranjo (2016) considers youth unemployment right after graduation as a reason for the relatively low take-up rate of student loans and suggests that, for instance, students need to have an unemployment compensation scheme within the loan program. A related effect is already implemented in the German student aid system: German students who received BAföG during their studies have a grace period of 5 years after the nominal end of their first degree. Afterwards, they can apply for an extension of this grace period if their income is below a threshold (1145 EUR for singles in 2018).

Students might also dislike the idea of bearing debt to such an extent that they rather do not take up student aid at all even though it would be clearly financially beneficial to them. In the student survey *21. Sozialerhebung*, 25% of all students who have never applied for BAföG state accumulating debt as a reason for not applying (Middendorff et al., 2017). Cunningham and Santiago (2008) find that family and societal characteristics matter for the degree of debt aversion. Some cultures have a very negative connotation when it comes to bearing debt, hence, they discourage students within their culture to make use of their right to apply for financial aid. Caetano et al. (2011) analyze the psychological aversion to debt and show that the labeling of student aid programs also matters for the take-up. The word “debt" is negatively perceived, intimidating students to apply for federal aid whereas “Human Capital Contract" seems to be a more agreeable term to promote student aid take-up. Eckel et al. (2007) point out that students might already have high debt levels that keep them from entering further debt contracts. Furthermore, Cadena and Keys (2013) substantially contribute to this behavioral framework by focusing on debt averse behavior that is based on a lack of self control. In principle, student loans smooth consumption over time. However, these additional financial resources might tempt students to overspend during study time in case they suffer from a lack of self control. In order to test this hypothesis, Cadena and Keys (2013) consider U.S. students and distinguish between individuals living on- and off campus, since students living off-campus receive a part of their aid in cash. Thus, off-campus students might be more inclined to spend their money on items and leisure activities that are not necessarily considered to be essential when it comes to basic living. With a linear probability model, they show that “students who live off-campus are 8.0 percentage points less likely to accept their loans than are students in the same financial situation living on campus". Therefore, a student without self-control might be better off by rejecting a zero interest loan in order to restrict overspending.

Herber and Kalinowski (2016) build a micro-simulation model to distinguish between actually eligible and non-eligible students, restricting their sample to the former group. They construct a "non-take-up rate", which constitutes the percentage of students who do not take up their aid entitlements even though they are eligible. Their basic results from the pooled probit model show that if the student's potential aid amount increases, the non-take-up rate decreases. For students who have older siblings that claimed BAföG before, the non-take-up rate decreases, which indicates that siblings mitigate the problem of information restrictions by helping their siblings and serving as a role model. Also, being impatient and impulsive increases the non-take up rate, which they interpret as debt averse behavior. Herber and Kalinowski (2016) focus on the effect of the potential aid amount on the probability of non-take up. Bearing this in mind, they take into account the possibility that endogeneity of the level of benefits affects their results, and hence, use empirical models like the IV probit, TSLS and Heckprobit.

Steiner and Wrohlich (2012) find that an increase of BAföG increases the average enrollment rate in higher education. However, their "estimate of a relatively small enrollment elasticity with respect to the amount of financial student aid implies that financial incentives alone will not achieve the policy goal of substantially increasing the share of students in university education within age cohorts at feasible fiscal costs" (Steiner and Wrohlich, 2012). This, once again, raises the question as to what other factors might drive the non-take-up decision of students.

We address this question by building a simple theoretical model to illustrate the interaction between imperfect information, risk attitude, and student income. We then derive several hypotheses and empirically test the interaction effect on the probability of non-take-up. Also, we rather take into consideration that our results might be driven by unobserved heterogeneity and hence, use the RE und CRE-models within the probit framework.

3 A Model of Student Aid

We build a simple model to illustrate a student's decision to apply for student aid conditional on risk aversion and debt aversion, student income, and information frictions. Assume momentarily that there are only two different outcomes of an application: high aid (with probability p) or low aid (with probability $1-p$). Let π_{ij1} be the total income as a student in period 1 (including student aid, costs of the application procedure and so on) where $i \in \{a, n\}$ denotes whether the student has applied for student aid ($i = a$) or not ($i = n$) and j whether the student receives high student aid ($j = h$) or low student aid ($j = l$). If the student does not apply ($i = n$), the payout will not depend on the realization of the potential aid, $\pi_{nh1} = \pi_{nl1}$. After graduation, the student enters the labor market and receives income π_{ij2} (including potential aid repayments). We use Epstein-

Zin preferences (Epstein and Zin (1989), Epstein and Zin (1991)) to separate the effect of risk aversion from the inter-temporal elasticity of substitution. Thus, expected utility of a student can be written recursively as

$$U_{ijt} = \left[(1-\beta)\pi_{ijt}^{1-\rho} + \beta(E_t U_{ijt+1}^{1-\alpha})^{\frac{1-\rho}{1-\alpha}}\right]^{\frac{1}{1-\rho}}, \tag{1}$$

where $0 < \beta < 1$ can be interpreted as the weight of future utility relative to present utility, ρ as the preference for intertemporal consumption smoothing and α as the degree of risk aversion. In order to apply these recursive preferences we assume that students decide in period 0 (right before starting their studies) whether to apply for student aid during their studies in period 1. There are no cash flows in the "initial period" 0 ($\pi_{ij0} = 0$). Now consider the utility of a student who decides to apply for student aid, U_{aj0}. With probability p, the student receives a high aid amount, giving rise to the payoff π_{ah1} during her studies and π_{ah2} after her studies. With probability $1-p$ she receives a low amount, generating the payoffs π_{al1} and π_{al2}. If we substitute this into (1), rearrange and reiterate, we obtain the expected utility

$$U_{aj0} = p\left[\pi_{ah1}^{1-\rho} + \beta\pi_{ah2}^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} + (1-p)\left[\pi_{al1}^{1-\rho} + \beta\pi_{al2}^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}}. \tag{2}$$

We assume that the exogenous non-aid-dependent income of the student is $\overline{\pi}_1$ and $\overline{\pi}_2$ in the two periods. Students receive the signal s at the beginning of period 0, correlated to the actual amount a the student would receive conditional on applying for aid. Moreover, a student who applies for student aid must spend additional time and resources $c > 0$ in period 1 to do so. As a benefit, the student will receive the additional amount a as student aid in period 1 and has to pay back $a/2$ in period 2. If the signal would be perfect and would reveal the correct student aid, that is, $s = a$, the utility of an application would be

$$U_{a0}(s) = \left[(\overline{\pi}_1 - c + s)^{1-\rho} + \beta(\overline{\pi}_2 - s/2)^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} \tag{3}$$

However, information frictions distort the actual signal s by some noise e such that $s = a - e$. We assume that this distortion e is uniformly distributed according to the density function

$$f(e) = \begin{cases} \frac{1}{2x} & \text{for } -x \leq e < x \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where the exogenous x can be interpreted as the extent of the information frictions. For $a > 2x$, even if the student receives the worst signal possible, she will still be sure to receive at least a positive amount of student aid. Thus, for sufficiently moderate information frictions, we do not need to consider the restriction that student aid cannot be negative.

If we consider the distribution of the signal according to (4), the expected utility must be aggregated over the different levels of e, giving rise to

$$U_{a0}(s) \quad = \quad \int_{-x}^{x} \left[(\overline{\pi}_1 - c + s + e)^{1-\rho} + \beta(\overline{\pi}_2 - (s+e)/2)^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} \cdot f(e)de \tag{5}$$

Proposition 1 *If* $\overline{\pi}_1 + \frac{3}{2}(s+x) < \overline{\pi}_2$, (5) *is strictly increasing in* s.

Proof of Proposition 1

$$\begin{aligned} U'_{a0}(s) &= \int_{-x}^{x} \frac{1-\alpha}{1-\rho} u(s)^{\frac{\rho-\alpha}{1-\rho}} \cdot [(1-\rho)(\overline{\pi}_1 - c + s + e)^{-\rho} \cdot 1 \\ &\quad +\beta(1-\rho)(\overline{\pi}_2 - (s+e)/2)^{-\rho} \cdot (-1/2)] \cdot f(e)de &(6) \\ U'_{a0}(s) &> 0 \; if \int_{-x}^{x} (\overline{\pi}_1 - c + s + e)^{-\rho} - \frac{1}{2}\beta(\overline{\pi}_2 - (s+e)/2)^{-\rho} de > 0 &(7) \end{aligned}$$

Now note that the minuend under the integral is decreasing in e*, while the subtrahend is increasing in* e*. Thus, a sufficient condition for* (7) *is*

$$\begin{aligned} (\overline{\pi}_1 - c + s + x)^{-\rho} - \frac{1}{2}\beta(\overline{\pi}_2 - (s+x)/2)^{-\rho} &> 0 &(8) \\ \overline{\pi}_1 - c + s + x &< \left(\frac{2}{\beta}\right)^{\frac{1}{\rho}} (\overline{\pi}_2 - (s+x)/2) &(9) \end{aligned}$$

For $\beta < 2$ *(usually we assume* $\beta < 1$*),* $c > 0$ *and* $0 < \rho < \infty$*, we obtain the sufficient condition from Proposition 1.*

Given a signal s, the student will apply for student aid if

$$\begin{aligned} U_{a0}(s) &\geq U_{n0} \text{ with} &(10) \\ U_{n0} &= \left[\overline{\pi}_1^{1-\rho} + \beta\overline{\pi}_2^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}}. &(11) \end{aligned}$$

According to proposition 1, the LHS of (10) is strictly increasing in s, while the RHS is constant. Thus, there exists a unique signal threshold $\overline{s}$ for which the student is indifferent between applying or not, implicitly defined by

$$U_{a0}(\overline{s}) = U_{n0} \tag{12}$$

Using the uniform distribution of s, we compute the probability that a student with the eligibility for the aid amount a finds it optimal to not apply for student aid:

$$\text{Prob(no application)}(\overline{s}) \quad = \quad \begin{cases} 0 & \text{if } \overline{s} < a - x \\ \dfrac{\overline{s} - (a-x)}{2x} & \text{if } a - x \leq \overline{s} \leq a + x \\ 1 & \text{if } \overline{s} > a + x \end{cases} \tag{13}$$

Simulation

We simulate the decision for students with different levels of risk aversion α, high and low information frictions x, and student income $\overline{\pi}_1$ varying from monthly 100 EUR up to 400 EUR[3]. We assume that the student under consideration would receive a rather moderate aid amount of 150 Euro a month, conditional on applying for student aid. In order to obtain significant rejection rates we need to assume significant application costs of 100 EUR.[4] All parameters can be found in table 1.

Parameter	**Interpretation**	**Value**
α	Risk aversion	0.9 (high) -1 (low)
ρ	Preference for intertemp. cons. smoothing	0.5
β	Time preference rate	1
$\overline{\pi}_1$	Income period 1	1 to 4
$\overline{\pi}_2$	Income period 2	20
c	Cost of applying for student aid	1
x	Information frictions	0.75 or 0.375
a	Student aid in case of application	1.5

Table 1: List of Parameters. Income $\overline{\pi}_1$ and $\overline{\pi}_2$, student aid a and costs c are in 100 EUR.

Figure 1 shows the outcome of the simulation for students with varying income $\overline{\pi}_1$ with a rather imprecise signal ($x = 0.75$) and a more precise signal ($x = 0.375$), holding risk-aversion $\alpha = 0.9$ constant. The simulation illustrates several hypotheses that can be derived from our basic theoretical model.

Hypothesis 1 *The probability to not apply for student aid is increasing in a students' income as this reduces the marginal utility of aid during her studies.*

Hypothesis 2 *The probability to not apply for student aid is increasing in the extent of information frictions.*

Figure 2 illustrates how more precise information (from $x = 0.75$ to $x = 0.375$) reduces the probability to decline student aid for students with different income levels.

Hypothesis 3 *The effect of information on the probability to decline student aid (Hypothesis 2) is stronger for poorer students. That is, the effect of a decline in x on Prob(no application)($\overline{s}$) (13) declines with $\overline{\pi}_1$.*

[3]These rather low income levels have no effect on the eligibility or amount of student aid.

[4]We show later that we can assume lower costs once we allow for debt aversion.

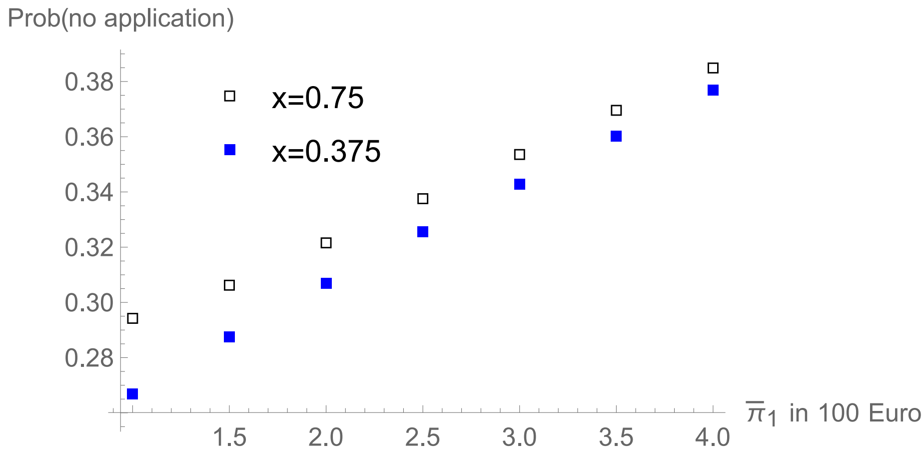


Figure 1: Prob(no application) for student with high risk aversion ($\alpha = 0.9$) and imprecise ($x = 0.75$) or more precise ($x = 0.375$) signal

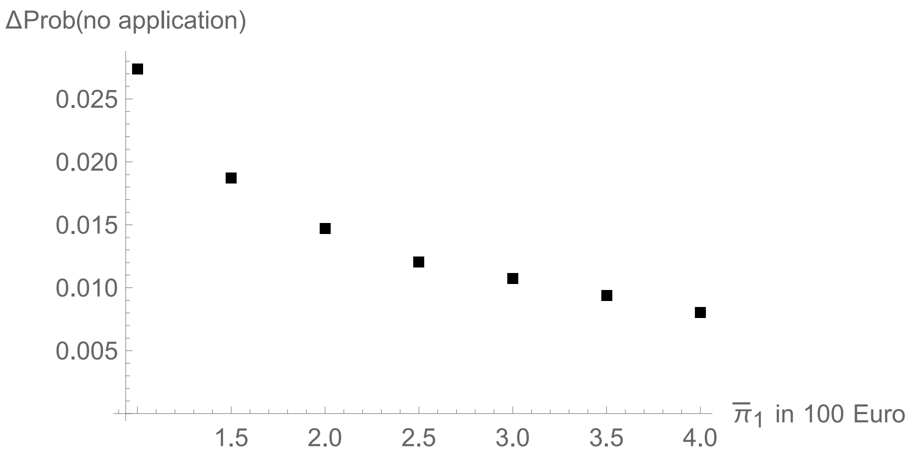


Figure 2: The effect of a more precise signal on the probability to decline student aid

So far we kept risk-aversion constant at a rather high level $\alpha = 0.9$. Figure 3 adds a student with low risk-aversion $\alpha = -1$ to figure 1. If we compare two students with identical income $\overline{\pi}_1$ and the same level of information frictions x, the more risk-averse student (squares) will always have the higher probability to decline student aid despite eligibility than the less risk-averse student (circles).

Hypothesis 4 *Students with higher risk-aversion are more likely to not apply for the "risky" student aid.*

Figure 4 illustrates the interaction between risk-aversion, income, and information more

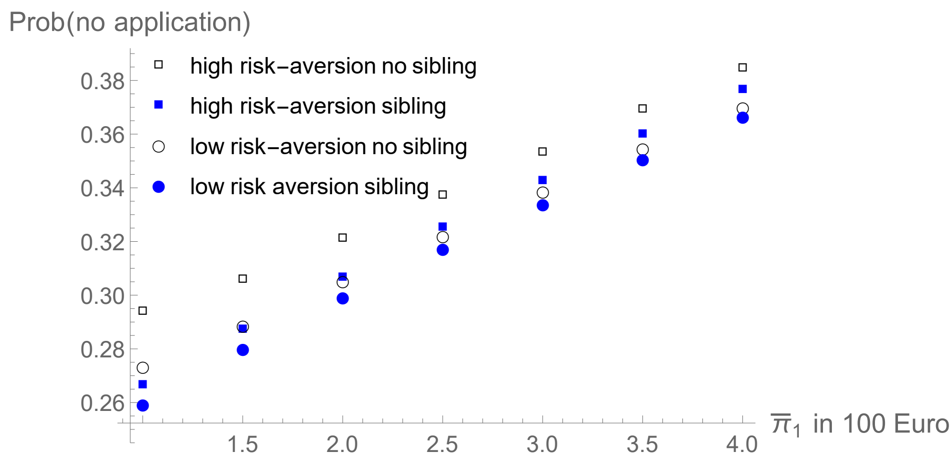


Figure 3: Prob(no application) for students with high risk-aversion ($\alpha = 0.9$) or low risk-aversion ($\alpha = -1$) and imprecise ($x = 0.75$) or more precise ($x = 0.375$) signals

in detail. While the effect of information on the probability to not apply for student aid declines with income for both types of risk-aversion, it is stronger and declines faster for more risk-averse students.

Hypothesis 5 *The effect of information on the probability to not apply for student aid is higher and declines faster with income for students with high risk-aversion.*

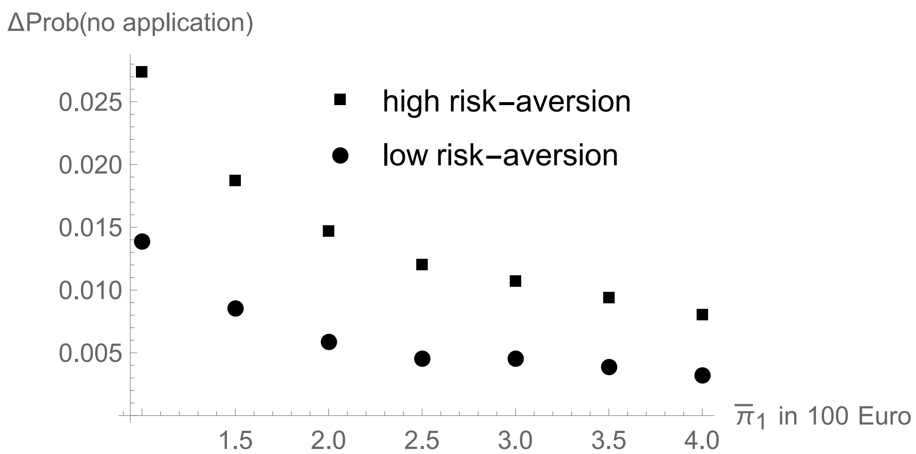


Figure 4: The effect of a better signal on the probability to decline student aid for students with high risk-aversion ($\alpha = 0.9$) or low risk-aversion ($\alpha = -1$)

A successful application for student aid does not only provide "free money", but it also comes with a significant amount of debt. As the *21. Sozialerhebung* (Middendorff et al.,

2017) and several studies suggest, aversion against this debt may well deter students from applying for aid, even if this significantly increases the present value of their income streams.

There are several ways to implement debt aversion into this model. If the effect of debt on utility is independent of the level of debt, we can modify (12) to

$$U_{a0}(\overline{s}) - \overline{d} = U_{n0}, \tag{14}$$

where $\overline{d}$ denotes the disutility of having any level of debt. However, we would expect that the disutility of owing debt is also increasing in the debt amount and modify (5) to

$$U_{a0}(s) \quad = \quad \int_{-x}^{x} \left[(\overline{\pi}_1 - c + s - d(s) + e)^{1-\rho} + \beta(\overline{\pi}_2 - (s+e)/2)^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} \cdot f(e)de, \tag{15}$$

where $d(s)$ denote the disutility caused by the debt level s, with $d(0) = 0$, $d'(s) > 0$ and $d''(s) > 0$.

The effect of debt aversion is rather obvious: An increase in general debt aversion $\overline{d}$ or an upward shift in $d(s)$ for all $s > 0$ raises the signal threshold $\overline{s}$ and reduces the probability that a student applies for student aid. This is summarized by

Hypothesis 6 *An increase in debt aversion reduces the probability to apply for student aid.*

4 Empirical Application

4.1 Data and Sample Construction

The SOEP (Socio-Economic Panel (SOEP), 2015) contains representative micro-data for Germany from 1984 onwards, covering a wide range of topics such as education, employment, income and health.[5] We restrict the observation period of the sample to the years $2001 - 2013$ and only include SOEP-respondents who were studying during the time of the survey and for whom it is traceable whether they received BAföG or not during their studies. Before 2007, it is not possible to distinguish between students receiving scholarships and BAföG payments, as one variable covers the receipt of both student funding schemes. Starting in 2007, the SOEP included a additional variable in order to explicitly identify BAföG payments. We use the variable that includes both funding schemes because this

[5]Goebel et al. (2019) provide an extensive discussion of the SOEP and its potential.

variable is available for the entire period from $2001-2013$ and only very few students receive scholarships in Germany.[6] We drop individuals for which we cannot identify parents, siblings and, if applicable, the partner. This restriction reduces our sample from 9,170 to 5,892 observations.

Unfortunately, the SOEP does not provide information on the actual eligibility of a student for BAföG, let alone the amount a student does or would receive after an application. Thus, we determine eligibility by simulating potential BAföG amounts using the formula suggested by Steiner and Wrohlich (2012):[7]

$$a = max\left(0, A - \frac{max(0, w - \bar{w})}{2} - \frac{max(0, p - \bar{p})}{k}\right), \tag{16}$$

where students' eligibility for aid amount a is a function of several variables. The upper limit for BAföG, A, is reduced if the student's main/side job income, w, exceeds the exemption threshold $\bar{w}$. The same logic applies to parental (and if married spousal) income, p, and the total exemption threshold for parental (and spousal) income, $\bar{p}$. $\frac{1}{k}$ determines the rate at which the deduction is conducted, starting at 0.50 for students who have no siblings and continuously increasing by 0.05 for each sibling under the age of 18. A detailed explanation of the simulation model including information on the maximum aid amount, A and income exemptions $\bar{w}$ and $\bar{p}$ is provided in the Appendix.

Eventually, the simulation leaves us with 4,238 observations for whom we simulate aid amounts, a. After considering age requirements, 4,057 observations (95.73%) are formally eligible for BAföG payments.[8] Among these eligible individuals, mean aid is estimated to be 345 EUR per month in the sample over the years $2001-2013$. This is reasonably close to Middendorff et al. (2017), who report a mean BAföG amount in 2012 of 436 EUR per

[6]For $2007-2013$, about 11% of the observations give contradictory answers, which might give rise to a measurement error in the dependent variable.

[7]A complex micro-simulation model is introduced by Herber and Kalinowski (2016) with an observation period set from $2002-2013$. The simulation by Steiner and Wrohlich (2012) includes previous years from $2000-2006$ and a more intuitive simulation model, which is not too complex and approximates student aid amounts. For instance, instead of considering siblings' income, siblings only increase parental income allowances.

[8]In practice, formal eligibility requires further information, such as whether the student passes obligatory exams during studies or whether the nominal length of studies is adhered to. Unfortunately, the SOEP does not contain any information on, e.g., the nominal length of a student's study program. Moreover, it is required that students are enrolled in their first-time study program. However, since we do not have any information on their previous degree level, we have to assume that they are enrolled in their first-time study program.

month, considering that our sample contains observations from the previous decade. We use the simulated aid amounts to create an indicator that shows whether observation i is eligible for a positive aid amount in period t:

$$\text{Eligibility}_{it} = \begin{cases} 1 & \text{if} \quad a_{it} > 0 \\ 0 & \text{if} \quad a_{it} = 0 \end{cases} . \tag{17}$$

Table 2 shows that 1,480 observations are simulated to be eligible (36.48%), whereas 2,577 are simulated to be non-eligible (63.52%). The numbers seem to be in accordance with Herber and Kalinowski (2016)'s results who consider within their 2,827 formally eligible observations 41% to be actually eligible and 59% to be non-eligible. For 370 observations (9.12% out of all formally eligible individuals), students report to receive BAföG even though the simulation estimated them to be non-eligible. As a comparison, the "wrongly estimated" cases (the beta-error) for Herber and Kalinowski (2016) accounts to 6% of their entire student sample. The different beta-errors may result from the fact that the simulation in this paper uses the approach of Steiner and Wrohlich (2012). As Herber and Kalinowski (2016) further emphasize, beta-errors may arise from the fact that the BAföG variable used also includes scholarships in the SOEP.[9]

Table 2: Simulation results

	Eligibility status		
BAföG recipient	Not eligible	Eligible	Total
No	2,207	985	3,192
Yes	370	495	865
Total	2,577	1,480	4,057

Source: SOEP data 2001 – 2013.

Choice of Variables

According to hypothesis 1 from the theoretical model, we expect that a student's non-aid income $\overline{\pi}_1$ (own labor income, transfer from parents) has a positive effect on the probability to not apply for student aid despite eligibility. A higher own income or transfer from parents makes it easier for a student to cover her expenses via other sources and reduces

[9]To test this hypothesis, we compute the beta-error by solely considering the "correct" 2007 – 2013 BAföG variable of the SOEP, which leads to a decrease of the beta-error to 5.03%.

her marginal utility of further income. Thus, she is more inclined to reject aid. Moreover, she might overestimate the effect of her own income or her parent's income on eligibility. Hypothesis 2 suggests that this effect should increase with information frictions. We will also be able to test for hypothesis 3, i.e., whether low income level students react more severely to changes in information than high income students in terms of their probability to reject BAföG.

We determine a student's non-aid income based on different income sources from the SOEP, including student income from main and side jobs, orphan payments, transfers received outside the household and child allowance payments. Note that transfers received by parents is unfortunately not provided in the SOEP. Hence, we simulate child allowance payments *Kindergeld* as a lower bound for parental financial help. In Germany, all students below the age of 25 years receive these payments. The *Kindergeld* simulation is only possible if information on siblings is available. The detailed computation method is available upon request. The final student income variable most likely entails a measurement error due to data restriction. We necessarily have to assume that missings on any of the student income sources imply that no income was received from theses sources, otherwise the already moderate sample size would decrease even further.

Next, we consider both parents' gross labor income. Conditional on the extend of information frictions, the student might overestimate the effect of increasing parental income on eligibility. A similar relationship might exist between student age and the probability to reject BAföG. Older students might falsely think that they are not eligible for federal student aid anymore, since they have little to no information concerning the age limit. Parents who have experience with higher education institutions are more familiar with the educational environment and thus, might have heard of BAföG or even received some sort of federal student aid themselves before. Parents with a college degree might find it easier to assist their children with an application for federal student aid than parents without an university degree. The same line of argument applies to siblings who are currently enrolled in higher education and also receiving BAföG. They can serve as source of information when it comes to the existence of such an aid scheme, answer questions or assist in the application process. We also include a migration background variable, considering that migrant parents might struggle with language barriers that keep them from being informed about potential federal student aid schemes.[10]

[10]Bear in mind that the variables introduced so far only concern the students' side. However, Strauss (1977) finds evidence that information offices in a county affect participation rates in social welfare pro-

In order to test hypotheses 4 and 5, we incorporate a variable including the attitude towards risk. In the personal questionnaires of the SOEP in 2004, 2006 and 2008 – 2013, risk aversion is covered by the question: "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" Respondents answer with values from 0 to 10, where 0 represents a high level of risk aversion and 10 translates into fully being comfortable to take on risk. Like Herber and Kalinowski (2016), we use this variable as measure for risk aversion, but handle missing data in a different way. In order to reduce the number of missings, we assume that the personal willingness to take on risk does not significantly change over time. If a student has information on her risk attitude for more than one year, we replace missing values and existing ones by a mean score of all of her answers over time. We recode the variable to a binary one, where $0-5$ stands for highly risk averse and $6-10$ for people willing to take on more risks (less risk averse).[11] According to Hypotheses 1 - 5, we expect that a student's rejection probability is determined by the combination of her income level, the amount of information about the BAföG scheme, as well as her attitude towards risk.

Lastly, in order to test for hypothesis 6, namely to test for the effect of debt aversion on the rejection probability, we add two additional explanatory variables to the regression. Note that the SOEP provides a variable that entails information on whether a student's family is repaying any monthly debt amounts: "Aside from debts on loans for home and property ownership, are you currently paying back loans or interest on loans that you took out to make large purchases or other expenditures?" An individual who is already familiar with debt should be more comfortable taking on debt, and thus is considered to be less debt-averse. According to Cadena and Keys (2013), students who live at home choose to do so because they are debt-averse and try to restrict their consumption. We consider this effect by adding an indicator that shows whether the student is living at home during her studies or not. [12]

grams. This hypothesis would have been interesting to consider within the BAföG aid scheme as universities might differ in their quality of communication and consultation. Unfortunately, there is no data available which tracks the quality of student aid assistance offices in Germany.

[11]Herber and Kalinowski (2016) include risk attitudes into their analysis as well, however, we go a step further and analyze several interaction terms, as will be explained in the following.

[12]Herber and Kalinowski (2016) also include a variable that determines whether a student is living at home. They argue that students' needs are lower when living at home. This paper rather emphasizes the fact that they restrict themselves in their consumption when still living at home.

4.1.1 Descriptive Statistics

The sample, which only includes eligible individuals, consists of a total of 1,480 observations with 677 students who are observed in an unbalanced panel over 13 years and appear on average more than three times. About 72.49% of students who receive aid in one year also receive it the year after, and about 89.27% of students who do not receive aid continue to not receive it the year after. This persistence suggests that students rather stick to their original decision and it is not likely that they will change their behavior during the course of their studies. The persistent behavior could also be driven by unobserved heterogeneity, which will be considered later on. For descriptive purposes we will only consider a smaller sample consisting of $N = 988$ observations ($n = 412$ students) that have no missings in any of the explanatory variables. As can be seen in table 3, half of the observations are female and the mean age is 23 years. About 1/4 of all cases/observations have a migration background and almost 1/3 live in East Germany. Half of the observations have at least one parent with a higher educational degree. The mean parental gross labor income equals 4,588 EUR per month, whereas mean student income equals reasonable 228 EUR per month (no BAföG included). Half of the cases display a rather risk averse behavior with the remaining half being less risk averse. Roughly 10% of the observations have siblings who were also receiving BAföG during the observation period. More than 2/3 of the cases are still living at home with at least one parent and approximately 22% report that the household they live in is currently in debt.[13]

4.2 Modeling the Probability of Rejection

Since the sample has already been reduced to only eligible students, the remaining part only entails to analyze how the probability of not applying for BAföG is affected by some explanatory variables. Hence, all results will be conditional on being eligible. We first construct the dependent variable NotApply_{it}, which equals 1 if eligible students do not apply for BAföG and 0 otherwise:

$$y_{it} = \text{NotApply}_{it} = 1 \quad \text{if student does not apply for BAföG.} \tag{18}$$

The dependent variable is observed for all time periods $t = 1, ..., 13$ for the unbalanced panel consisting of $i = 1, ..., 412$ students. The binary nature of the dependent variable suggests a binary response model. Hence, the probability not to apply for BAföG can be

[13]The Appendix provides some additional information on coding and also the level of measurement concerning explanatory variables.

Table 3: Descriptive statistics

Variable	Mean	SD	Min.	Max.
Dependent				
NoBAföG	0.66	0.47	0	1
Explanatory				
Female	0.49	0.5	0	1
Age	23.36	2.38	17	30
East Germany	0.33	0.47	0	1
Migration background	0.27	0.45	0	1
Parent(s) has/have university degree	0.47	0.5	0	1
Gross parental labor income (in 100 EUR)	45.88	14.55	12.4	115.6
Student income (in 100 EUR)	2.28	2.5	0	17.71
Less risk averse	0.47	0.5	0	1
Siblings receiving BAföG	0.1	0.3	0	1
Household pays back monthly credit	0.22	0.41	0	1
Lives with at least one parent	0.69	0.46	0	1
Observations ($= N$)		988		
Students ($= n$)		412		

Source: SOEP data 2001 – 2013. *Notes*: Income measured on a monthly basis. The siblings variable only equals one if students have siblings who also received BAföG during the observation period.

modeled as follows:

$$\mathrm{P}(\mathrm{NotApply}_{it} = 1|\mathbf{x}_{it}, c_i) = \mathbf{\Phi}(\mathbf{x}_{it}\boldsymbol{\beta} + c_i). \tag{19}$$

Note that $\mathbf{x}_{it} = (x_{i1}, ..., x_{iT})$ is a vector for the full set of explanatory variables and $\boldsymbol{\beta}$ represents the vector of parameters. The response probability takes on values strictly between zero and one, following the standard normal distribution function $\mathbf{\Phi}(.)$. The individual specific time invariant trait, c_i, is unobservable. Another way to think about a binary response model is to consider a latent variable formulation, where the variable of interest is actually non-observable (Wooldridge, 2013). Imagine that we are actually interested in a student's utility both for an application and non-application. If the utility for a non-application exceeds the expected utility of an application, the student will choose not to apply, illustrated by equation (10) in the theoretical model. Both (expected) utilities of students are not observable but the actual outcome is. The latent variable can be expressed as

$$y_{it}^* = \mathbf{x}_{it}\boldsymbol{\beta} + e_{it} \tag{20}$$

$$y_{it} = 1[y_{it}^* > 0] \tag{21}$$

$$e_{it} = c_i + u_{it}, \quad u_{it}|\mathbf{x}_{it} \sim \text{Normal}(0, 1), \tag{22}$$

where y_{it}^* stands for the unobserved difference in utilities and determines the choice of the student. More specifically, the indicator function 1[.] in expression (21) takes on the value 1 (student does not apply for BAföG) if y_{it}^* is positive (Wooldridge, 2013). This is only the case if the utility from not applying for BAföG will be greater than applying for it, and 0 otherwise. The composite error, e_{it}, consists of an individual unobserved time invariant, c_i, and a time-varying part, u_{it}, as can be seen in equation (22) (Longhi and Nandi, 2015). Note that the time-varying part, u_{it}, is assumed to be i.i.d. with mean 0 and variance 1. Furthermore, u_{it} and $\mathbf{x}_{it}$ are assumed to be independent (Wooldridge, 2010). Assumptions concerning the individual time invariant traits, c_i, depend on the model specification.

The general formulation of the probit model allows us to start off with a basic pooled estimation, disregarding the fact that we have panel data. The total size of the pooled sample equals $N = 988$ observations, where students are treated to be independent observations even though on average they appear multiple times in the sample. In addition, the transition rates show high persistence, i.e., students are likely stick to their decision throughout their entire university career by either applying for BAföG or not. First of all, it is obvious that the assumption of independent observations is rather misleading. Secondly, the persistent behavior of students might be indeed partly explained by some explanatory variables. However, there might also be some unobserved heterogeneity that drives the decision of students. If this is indeed the case, the composite error term for a student is serially correlated. Only if there is no individual effect or the individual effect is the same for every observation, the parameters can be consistently estimated by pooled probit (Andreß et al., 2013):

$$c_i = 0 \quad \text{or} \quad c_i = c \,\forall\, i \quad \text{or} \quad \sigma_c^2 = 0. \tag{23}$$

With that being said, we cluster observations over personal id's and compute standard errors robust to serial correlation with the underlying pooled data available (Andreß et al., 2013). According to Andreß et al. (2013), "treating the serial correlations of repeated observations as a nuisance factor by using robust standard errors is not very convincing because it only treats the symptoms and not the causes of the statistical dependencies." Therefore, we continue with estimation strategies that recognize the panel structure and deal with unobserved heterogeneity. First, using panel data allows us to deal with unobserved heterogeneity and decrease the size of possibly biased estimates. For instance, a student's general motivation to study might determine her choice whether to apply for aid. Therefore, a student who is more motivated might be better informed and therefore, her individual probability of applying for BAföG is higher compared to c.p. less motivated students. Motivation is a personality trait that usually does not change significantly over time, such that it might serve as candidate for unobserved individual specific heterogeneity. However, motivation itself cannot be observed and it is captured in the error. Thus, the problem of serial correlation would arise. If assumption (23) does not hold, pooled estimates are inconsistent (Longhi and Nandi, 2015).

The following estimation strategy depends on the assumptions made on an individual's specific characteristics. One option is to continue with a random effects (RE) estimation, where it is assumed that

$$c_i|\mathbf{x}_i \sim \text{Normal}(0, \sigma_c^2). \tag{24}$$

Note that c_i and $\mathbf{x}_i$ are assumed to be independent and c_i is assumed to follow a normal distribution for the probit random effects model. If unobserved heterogeneity is assumed to be uncorrelated with the explanatory variables, c_i is rather seen as some sort of random variable; this, however, is a very strong assumption. Imagine that student motivation is partly correlated with a student's income, as more motivated students might also be more inclined to work while studying in order to earn an additional income. Eventually, this correlation would translate into existing endogeneity. However, the RE estimation rules out endogeneity and a failure of this assumption would lead to biased estimates. This already indicates that RE estimation is considered to entail restrictive assumptions as well. The advantage of preferring a RE model over a pooled probit model is that the panel structure is recognized and hence, serial correlation in the composite error is allowed. As introduced above, using pooled estimation within this framework ignores the fact that student observations are actually dependent, hence, standard errors will be too small (Andreß et al., 2013).

What can we do if unobserved heterogeneity is indeed correlated with the explanatory variables affecting the probability of a non-application? First, consider a fixed effects (FE) estimation. In linear models it is straightforward to eliminate c_i, for instance, through a within-transformation. However, our underlying model is not linear and thus, a within-transformation does not eliminate c_i. While we could add individual dummies to control for individual effects, the estimates would not be consistent as the number of parameters goes to infinity (incidental parameters problem) (Wooldridge, 2010). Within the probit framework there is no way for us to obtain consistent estimates with a FE approach. Moreover, one of the main variables contains information on risk averse behavior of students, which is assumed to be time-invariant. The parameter estimate for risk aversion would simply be omitted.

Fortunately, Wooldridge (2010) points out that there is a mid-solution, the Chamberlain's correlated random effects probit model (CRE probit). In contrast to FE, the CRE probit model allows for some correlation between the unobserved c_i and the explanatory variables by assuming that

$$c_i = \psi + \bar{x}_i \xi + a_i, \quad a_i | x_i \sim \text{Normal}(0, \sigma_a^2), \tag{25}$$

where unobserved heterogeneity is a linear function of the time averages of all time variant explanatory variables, $\bar{x_i}$, with ξ representing the vector of parameters for these averages. The error a_i is assumed to be independent of all explanatory variables and follows a standard normal distribution representing the "pure random effect". Note that only the effects of time-varying elements in $\bar{x}_i$ are estimated, so there should not be any time constant explanatory variables included into the model. If the model, however, contains a time-constant explanatory variable (e.g. risk aversion), it can still be included as an explanatory variable, subject to the condition that c_i is partially assumed to be uncorrelated with risk aversion. Furthermore, note that time dummies do not vary across observed units and they are omitted from $\bar{x_i}$. Essentially, the mean of (time-variant) explanatory variables for each unit i is added as a control variable to the original equation, which allows us to estimate the effect of explanatory variables while holding time averages fixed. A nice feature of the CRE probit is that we can test for the usual RE probit model by simply considering $H_0 : \xi = 0$, which leads the model to collapse to the usual random probit model. If we can reject H_0, the pure RE probit model should not be used (Wooldridge, 2010).

Results

Table 4 shows the results of the three models with both coefficients and average marginal effects (AME's). The overall significance of the model is given for all three models at a 0.1% significance level. First, consider the pooled estimation in the first column. Relative to the other two models, the standard errors of the marginal effects are small, which might be based on the assumption of independent observations. The percentage of correctly specified values equals 76%. As can be seen, the pseudo-R-squared for the pooled model equals 19.5%, which is rather high and suggesting that the model specification is good in explaining the rejection probability of students. We use personal controls including gender, age, region and migration background. In contrast to Herber and Kalinowski (2016) who find no evidence for an "age-affect", we find that the older a student, the more probable it is that she rejects aid. Some of them might (falsely) assume that they are not eligible due to their relatively advanced age (information gap) and hence do not apply. Living in eastern states the P(NoBAföG) decreases by 14.2%. Herber and Kalinowski (2016) argue that in theory, the effect of living in East Germany is ambiguous. On the one hand, people in the former socialist states might have lower financial literacy, which would translate into less information and increase non-take up in the East. On the other hand, people living in former socialist states might feel more entitled to public subsidies, which would give rise to a negative effect on non-take up. Our result provides evidence for the latter hypothesis.

After controlling for personal characteristics and regional differences, the main effects are tested for. If parental income increases by 1%, the probability not to apply for BAföG increases by 34.4% at a 0.1% significance level, as opposed to the results by Herber and Kalinowski (2016), who find no effect for this specific source. This result provides evidence that students whose parental income is c.p. higher expect (falsely) not to be eligible for BAföG and hence, refrain from applying. Thus, information frictions might play a role. Parents with a degree from higher education institutions might decrease the information gap of eligible students. However, the marginal effect is insignificant at any conventional significance level.

In line with Hypothesis 1, an increase in student income seems to have a small but significant (at $p = 0.001$) effect on the rejection probability. More specifically, if student income increases by 100 EUR, the probability to reject BAföG increases by 2.5% if the student is simultaneously highly risk averse and has siblings who could provide information on actual eligibility for student aid. In order to determine the relationship between information, income and risk aversion, we add two-way and a three-way interaction variable that shows whether the student has any siblings receiving BAföG, a student's attitude towards risk as well as her personal income owned. A test for the three-way interaction term turns out significant at a 0.1% significance level. Solely interpreting the AME's of each variable on

Table 4: Estimation Results

	(1) Pooled probit Coeff.	(1) Pooled probit AME	(2) RE probit Coeff.	(2) RE probit AME	(3) CRE probit Coeff.	(3) CRE probit AME
Female	-0.130 (0.122)	-0.038 (0.036)	-0.142 (0.258)	-0.026 (0.047)	-0.239 (0.273)	-0.040 (0.046)
Age	0.113*** (0.026)	0.033*** (0.007)	0.241*** (0.051)	0.044*** (0.008)	0.526*** (0.089)	0.088*** (0.013)
East	-0.485*** (0.146)	-0.142*** (0.042)	-0.974** (0.311)	-0.179** (0.055)	-1.857* (0.856)	-0.312* (0.139)
Migration background	-0.252 (0.160)	-0.073 (0.047)	-0.450 (0.326)	-0.083 (0.060)	-0.159 (0.348)	-0.027 (0.059)
Information & Risk						
Parental gross labor income (log)	1.179*** (0.214)	0.344*** (0.057)	2.174*** (0.412)	0.400*** (0.065)	1.091 (0.899)	0.183 (0.150)
Parents have university degree	-0.038 (0.135)	-0.011 (0.039)	0.181 (0.280)	0.033 (0.051)	0.138 (0.297)	0.023 (0.050)
Highly risk averse	-1.333* (0.520)	0.122** (0.037)	-2.461** (0.823)	0.137** (0.049)	-2.058* (0.853)	0.142** (0.046)
No sibling receives BAföG	0.103 (0.307)	0.305*** (0.059)	-0.103 (0.524)	0.336*** (0.065)	0.032 (0.545)	0.217* (0.084)
Highly risk averse × No sibling receives BAföG	1.740** (0.553)		3.286*** (0.847)		2.974*** (0.875)	
Own income	-0.126 (0.116)	0.025*** (0.007)	-0.303 (0.236)	0.025** (0.009)	-0.064 (0.259)	0.022* (0.010)
Highly risk averse × Own income	0.494** (0.177)		1.137*** (0.332)		0.953* (0.372)	
No sibling receives BAföG × Own income	0.190 (0.120)		0.416+ (0.242)		0.151 (0.258)	
Highly risk averse × No sibling receives BAföG × Own income	-0.456* (0.188)		-1.112** (0.340)		-0.919* (0.382)	
Debt Aversion						
Household pays back credit	-0.237+ (0.141)	-0.069+ (0.041)	-0.345 (0.220)	-0.063 (0.041)	-0.038 (0.281)	-0.006 (0.047)
Lives with at least one parent	0.388** (0.146)	0.113** (0.042)	0.617* (0.260)	0.113* (0.048)	0.483 (0.424)	0.081 (0.071)
Year controls	Yes		Yes		Yes	
Mean time variant variables	No		No		Yes	
Pseudo R^2	0.195					
ρ			0.768		0.780	
σ_c			1.821		1.881	
Observations ($=N$)	988		988		988	
Students ($=n$)			412		412	

Source: SOEP data 2001 − 2013. *Notes*: Income measured on a monthly basis, (own) student income in 100 EUR. Also, the "no sibling receives BAföG variable" includes students who have no siblings at all (during observation period). Robust standard errors in parentheses and significance given by $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

its own does not provide any important insights and is not really realistic. For instance, one might think that for students who do not have any siblings receiving BAföG, the probability not to take up BAföG increases by remarkable 30.5% (significant at 0.001-level).

However, we should be cautious with this interpretation, as the effect is only valid if the student has low aversion (base level for risk averse dummy) and an income equal to zero. Nevertheless, this is evidence in support of hypothesis 2. Similarly, the effect of the dummy variable depicting a student's risk aversion is only valid if the student has siblings who receive BAföG (base level for siblings dummy) and student income equals zero. However, the effect still seems to capture what is expected according to Hypothesis 4, namely, that for students of high risk aversion, the probability to reject BAföG increases by 12.2% at a significance level of 1%.

Consequently, all two-way and the three-way interaction terms can be explained in the same manner. The crucial part for the interpretation is to obtain correct AME's of the three-way interaction term, which makes the interpretation more complex than its two-way counterpart. For the interpretation, we decide to vary the level of income between $100 - 500$ EUR and set the level of risk aversion once to high and once to low in order to get the AME's of the "no siblings variable". The AME's are listed in table 5. Irrespective of their level of income, the absence of siblings who could provide additional information only has a moderate effect on the rejection probability of low risk averse students (at any conventional significance level). Conversely, for high risk averse students with low income ($100 - 300$ EUR), information frictions have a highly significant effect ($0.1\% - 1\%$ level) on the P(NoBAföG) as suggested by Hypothesis 5. For instance, for a highly risk averse student with a monthly income of 300 EUR, the probability of non-application increases by 32.7% at a significance level of 1% if she has no siblings receiving BAföG, i.e., if less information on BAföG is available.

The relationship between income, risk and information can be illustrated via a diagram that shows the predicted probabilities depending on the variable interaction. Both graphs in figure 5 depict the probability of not applying for BAföG for different combinations of income, information and risk aversion. For both groups, the rejection probability when having no siblings receiving BAföG (or no siblings at all) is higher than the rejection probability when they have siblings who receive BAföG (Hypothesis 2). However, the effect is stronger for students with high risk aversion (Hypothesis 5). For instance, for risk averse students with an income level equal to 200 EUR, the probability to reject BAföG is predicted to be 33.8% (significant at a 1% level) as opposed to students who have no siblings receiving BAföG or no siblings at all, where the probability is predicted to be 76% (at p-value $= 0.0001$).

Table 5: AME's of having less information depending on the level of risk aversion

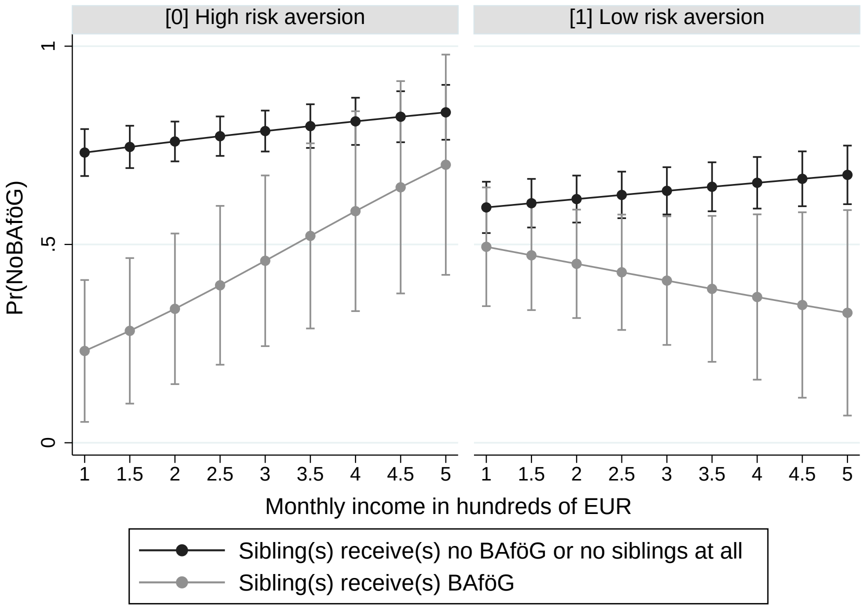
	AME's of having no siblings receiving BAföG or not having any siblings at all	
	High risk aversion	Low risk aversion
1. at income = 100 EUR	0.500***	0.099
	(0.098)	(0.082)
2. at income = 200 EUR	0.422***	0.163*
	(0.102)	(0.075)
3. at income = 300 EUR	0.327**	0.226**
	(0.115)	(0.088)
4. at income = 400 EUR	(0.115)+	0.288**
	(0.134)	(0.111)
5. at income = 500 EUR	0.132	0.348*
	(0.148)	(0.137)
N	988	

Source: SOEP data 2001 – 2013. *Notes*: AME's from pooled probit. Standard errors in parentheses and significance given by $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

For students with low risk aversion, additional information via siblings has a weaker effect than for students with high risk aversion. In line with hypothesis 4, the predicted probabilities curve for low risk averse students when having no siblings lies lower than the curve for high risk averse students'. Low risk averse students are expected to be less "worried" and hence show smaller estimated probabilities for rejecting BAföG over all income levels. In line with Hypothesis 1, a rise in income increases the predicted rejection probability continuously in almost all cases. As an exception, the curve for students with low risk aversion and siblings receiving BAföG is downward sloping. We would have expected a more flat curve, and hence no responding to different income levels. However, this result is based on a relatively small number of observations.

The results for the three-way interaction term seem to undermine the expected effects from theory referring to information restrictions and risk aversion. In contrast to our estimation, Herber and Kalinowski (2016) find no significant effects for parental income and degree, also attitude towards risks seems not to have a significant effect on the Pr(NoBaföG). In line with our results, their siblings-variable clearly shows significant effects on the probability of non-take up. Our model combines the information-income-risk dimension and finds a significant relationship of the effects on the Pr(NoBAföG).

Figure 5: Predicted probabilities of turning down BAföG depending on student income, information gap and risk aversion



Source: SOEP data 2001 − 2013. *Notes:* Depicted are the predicted probabilities of students rejecting BAföG depending on their level of income, risk averse behavior and information level of BAföG with 95% confidence intervals (CI's). The dummy variable of students not having any siblings receiving BAföG also contains students who do not have any siblings at all.

If the student belongs to a household which pays back a credit on a monthly basis, the probability to reject BAföG decreases, supporting Hypothesis 6; however, the effect is only significant at 10% significance level. Students living at home have a 11.3% higher probability to reject BAföG (significant at 1% level). This is in line with the hypothesis that students living at home tend to be more cautious in their spending in order to prevent overspending/debt accumulation. Herber and Kalinowski (2016) use an interaction between impulsivity and impatience of students to attribute the effect of debt aversion and also find significant effects.

The RE probit model serves as comparison in the second column of table 4. To see whether unobserved heterogeneity plays a significant role, we consider the estimated variance of unobserved heterogeneity relative to the total variance of the overall error. In the probit model, the variance of the composite error is $\sigma_e^2 = 1$ and the estimation of $\hat{\sigma}_c^2 = 1.821$. This yields a $\hat{\rho} = 0.768$, so 76.8% of the variance in the error is attributed to the variance of unobserved heterogeneity. This explains why we should consider the RE in addition to a normal pooled probit. Moreover, a likelihood ratio test testing for non-existence of unobserved heterogeneity can be rejected at a 0.1% significance level. With respect to personal controls and regional differences there is not much difference in the estimation, the magnitude simply increases for 3 out of 4 variables. Both the effects of the three-way interaction term and variables determined to effect debt averse behavior do not change very much. However, as already discussed, we should be cautious with these results, as RE assumes that explanatory variables are not correlated to the composite error term, which includes unobserved heterogeneity. A failure to include this assumption leads to biased estimates.

To relax this assumption, we consider now the CRE results in the third column of table 4. Again, there is evidence that individual specific traits play a role as $\hat{\rho} = 0.780$. A likelihood ratio test, testing the non-existence of unobserved heterogeneity can be rejected at a 0.1% significance level. Regarding personal and regional variables, note that especially the effect of the age-variable increases (8.8% instead of 3.3% for the pooled probit at a 0.1% significance level). Moreover, the east dummy increases in its magnitude but decreases in significance. The effect of parental income becomes insignificant in the CRE model, which might suggest that the effect was driven by unobserved individual specific traits being correlated with parental income. Hence, the question remains what characteristics of students might be student specific, time-invariant and correlated with parental income thus, eventually also affecting student choice?

In general, some variable effects become insignificant, which might be due to the fact that they were driven by individual effects which were correlated with the same explanatory variables changing their signs in the CRE and thus, affecting Pr(NoBAföG). To test whether individual specific traits indeed matter, we apply a testing approach suggested by Wooldridge (2010), where $H_0 : \xi = 0$, i.e., the vector of parameters of time variant explanatory variables equals zero. We can reject H_0, hence, proving a correlation between explanatory variables and unobserved heterogeneity. Unfortunately, the rather small sample might also be the reason for the moderate estimation power.

Sensitivity Analysis and concerns

As a robustness check, we additionally simulate eligibility by not considering own student income as an additional restriction, which obviously gives rise to a larger student sample (N=1,019). Figure A.1 depicts the predicted Pr(NoBAföG) for the new simulation. The results show that especially for low risk averse students, the predicted probabilities to different income levels is smaller, and the curve flatter than the original graph in 5.

Herber and Kalinowski (2016) use the aid amount as explanatory variable, which they find to be highly significant. As a robustness check, we include the additional variable into our model in table A.5 (first column). This does not significantly add explanatory power to predict the probability of not receiving BAföG. The coefficient for aid amount is small but still significant at a 1% significance level: An increase of the aid amount by 100 EUR reduces the probability to reject BAföG by 3.1%. With respect to the remaining variable estimates, the inclusion does not change the direction of the estimates and only affects slightly the significance levels. However, note that in contrast to Herber and Kalinowski (2016), we do not control for endogeneity of the benefit amounts.

In the second column, we analyze the same estimation equation with the dependent variable only considering the reception of BAföG (in contrast to the "combined" variable that includes BAföG and scholarships), which is only available for $2007 - 2013$, reducing our sample size to $N = 377$. This shortcoming already suggests that this version of the model might not provide reliable results. Comparing the estimated AME's to the pooled probit results in column 1 of table 4 does not provide significant differences to the main model.

The results of our main estimation are subject to several assumptions and restrictions. Missing information on the family background makes it difficult to collect information on e.g. parental income. The original student sample for the $2001 - 2013$ observation period declines from 9,170 to 5,892 observations because parents, siblings and, if applicable, the partner of an individual cannot be identified. We are not able to make any statement as to how random this decrease in sample size might be. Still, there is no specific reason why we would expect that this should give rise to a sample selection problem.

The basis for the regression is a simulation, which might have partly produced inaccurate estimates according to the beta-error. The approximation only grasps general eligibility by considering variables that are available in the SOEP. Take, for instance, information on parental net monthly income, which is one of the most important determinants in our regression model. However, the SOEP only measures taxes and social security contributions on the household level. Hence, we deduct only half of taxes and social security contributions reported in the SOEP if parents are separated and deduct the entire amount if parents are married and living together. Also, there is not always full information on all six different income sources. In these cases, we assume that no income was received by the respective income source if no information is available. Moreover, some students give contradictory answers regarding their BAföG status. Some of them state to receive BAföG but then, in following parts of the questionnaire, they do not report any monthly BAföG income.

5 Conclusion

Our simple theoretical model shows how it can be optimal for rational students to not apply for BAföG even though they would be eligible for a positive aid amount, including a free subsidy: Information frictions can deter students from filing for aid, while the effect is stronger for poorer students and more risk averse students. Moreover, debt aversion should reduce the take-up rate even further. With data from the SOEP, we simulate the eligibility status of each student in the sample and only keep eligible individuals. We apply a pooled probit model and, to control for unobserved heterogeneity, a RE probit and CRE probit model. In all models, the main effects do not vary much. An increase of parental income by 1% raises the probability not to apply for BAföG by 34%, suggesting that information frictions play a role in the take-up decision. The interaction of the three-way variable between a student's level of information (depending on siblings), the attitude towards risk and student income is highly significant at 0.1% for any of the models. Students who are more risk averse are stronger affected by information frictions. For them, having siblings who receive BAföG, decreases their predicted probability to not apply for BAföG, particularly significantly at lower income levels. Students who are less risk averse are less affected by information frictions. Moreover, students whose families are currently paying off any debt, which we consider to be less debt averse, seem to be more likely to apply for student aid, even though the effect is just marginally significant.

Middendorff et al. (2017) report that 37% of students from lower educational backgrounds state that making debt was the main reason for non-application. This suggests debt averse behavior that is especially pronounced for students from lower educational backgrounds. Moreover, as Glocker (2011) shows, the probability of finishing university successfully increases when students receive BAföG. A policy that aims to subsidize poor students, independent of their attitude towards risk, must take these effects into consideration. One way to inform students earlier and more efficiently about the BAföG scheme is to already advise high school students on the possibilities to receive federal student aid. A clear communication about the application process, what the repayment scheme looks like and also emphasizing that information centers exist can decrease information frictions and resolve misconception about eligibility. Even though our results show that highly risk averse behavior increases non-take up, they also show that it is possible to decrease this effect once more information for students is available. However, even if information among students would be perfect, some individuals might still dislike the idea of bearing debt so much that they refrain from applying because they know that they will pay back a part of the aid at some point in the future. One suggestion for these highly debt averse students might be to let them decide between a loan-grant BAföG scheme and a grant-only BAföG scheme. As such, students with very high debt averse behavior would accept the grant-only BAföG (obviously receiving only half of their actual aid entitlements) and thus, more students could be reached.

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Appendix

Simulation

Table A.1 shows the maximum aid amounts, A, that change over time due to several BAföG reforms in 2001, 2008 and 2010 and also depend on some personal-specific traits to be explained below. To compute A, we first need to identify whether students still live “at home" together with at least one parent. Thus, we compare the current household number of them with that of their parents’. If students live alone, we add an additional allowance to their basic needs, which is obviously only possible if information on the current household number is available. We use the rent that is paid by students to determine whether they are eligible for an additional high-rent allowance. If information on rent is missing out, we necessarily have to assume that no rent was paid by these students, as otherwise the sample would decrease too much. Some students pay mandatory payments to health insurance companies. If this is the case, they receive an additional health insurance allowance. Furthermore, payments that cover long term care insurance are collected by students. Moreover, students with children under the age of 10 receive additional payments. Thus, we collect data on the birth year of their children and consider the total number of children under the age of 10 for each student to add the respective payments on top of their basic needs.

Table A.1: A - Students’ maximum aid amount (in EUR/month)

	$2001-2007$	$2008-2009$	$2010-2013$
Basic needs if living at home	377	414	422
+ Living without a parent	89	98	175
+ High rent allowance	64	72	-
+ Health insurance allowance	47	50	62
+ Long term care insurance	8	9	11
+ First child allowance	–	113	113
+ Further children allowances	–	85	85
$= A$			

Source: Deutscher Bundestag (2014); Deutsches Studentenwerk (2008). *Notes*: Students get rent allowances if rent>133 EUR for $2001-2007$ or rent>146 EUR for $2008-2009$. Starting in 2010, the additional aid amount for rent was canceled. Health insurance allowance is only then granted if students are insured individually. Furthermore, to receive child allowances the age of children has to be under 10 years.

Table A.2 shows p, the parental (and spousal) income net of taxes and social security contributions.[14] According to the German Income Tax Law (*Einkommenssteuergesetz (EStG)*), there are seven different income sources considered for the computation of taxable income in Germany. We follow the approach by Baumgartner and Steiner (2004), who consider income tax and social security contributions at the household level for the computation of net parental income, since both, income tax and social security contributions, are reported in the SOEP.

Table A.2: p - Net parental income and if applicable, spousal income (in EUR/month)

Income sources of father, mother and if applicable, spouse
Gross labor income
+ Income from self-employment ⋄
+ Income from rent and lease
+ Capital income (dividends and interest) ⋄
+ Pensions
+ Unemployment benefits *(ALG II)*
= Gross income parents and spouse
− Income taxes ∘
− Social security contributions ∘
$= p$

Source: SOEP data $2001-2013$. *Notes*: ⋄ Capital income and income from self-employment are measured on a yearly basis. Hence, we compute the monthly mean. ∘ Income taxes and social security contributions are measured at the household level. In case parents are not married we only consider half of the income tax and social security contributions from each parent.

The first step entails to check whether parents are married and living together. If so, we add up the relevant income sources listed in table A.2 and subtract household taxes and social security liabilities at the household level. We check whether married parents report the same amount of household taxes and social security contributions. If parents are not living together, we add mother and father income and deduct half of the household taxes and social security liabilities that they report, respectively (as they could be in a new relationship and might have another spouse). Furthermore, if students are married and given there is information on the spouse's income, we add their income net of taxes and social security contributions to parental income. For both parents and spouses there is not

[14]In the SOEP some of the students' parents are already deceased during the time of the survey and for multiple cases parental income is still reported. Hence, we do not consider the death of a parent if we see that parental income is still reported for them. Nevertheless, we still include their reported incomes to the simulation process.

always information on all six income sources. Hence, in order not to lose too many observations we solely add income sources to their income variable for which positive amounts are available. Otherwise, we assume that no income was received through these sources. This approach potentially might lead to measurement error in the income variable, however, we do not suspect it to be too problematic in regards to this analysis, since it will be explained in the empirical analysis more in detail. Note that there are two different sources of variables in the SOEP to identify students' partners, namely marital and the partner status. Comparing these variables it becomes obvious that the respondents give contradictory responses, which might again be a source of measurement error. For some of the parents' and partner's income less taxes and social security contributions are simulated to be negative. We replace these values by missings, in order to avoid including misleading income levels. Relative to the sample size, these are, however, negligible for parents. In contrast to that, for partners there is already very little information to be begin with and further exclusion of misleading income simulations leads to even more missing values.

Any parental and spousal income that exceeds the threshold $\bar{p}$ that is reported in table A.3 reduces the students' aid entitlements. For each student we check whether parents are married and living together. If they are separated, we add the respective amount for basic allowances and further determine whether an individual has siblings under the age of 18. If so, we add the aid amount for additional siblings. Furthermore, the threshold income increases depending on the marital status of students, i.e., if students are married, we increase the threshold respectively and also take into account if they have any children. For the deduction of parental income, the number of their children under the age of 18 also matters. This is taken into account in the formula via the deduction parameter $\frac{1}{k}$. If students have no siblings, $\frac{1}{k} = 0.5$ and continuously increases by 0.05 for each additional sibling. Thus, the more siblings individuals have, the less will be deducted.

Table A.3: $\bar{p}$ - Threshold income parents/spouse (in EUR/month)

	2001 – 2007	2008 – 2009	2010 – 2013
If parents are married and living together	1440	1555	1605
+ If parents are separated (additional amount)	520	1040	1070
+ For each sibling under the age of 18	435	470	485
+ If students are married	480	520	535
+ For each child	435	470	485
= $\bar{p}$			

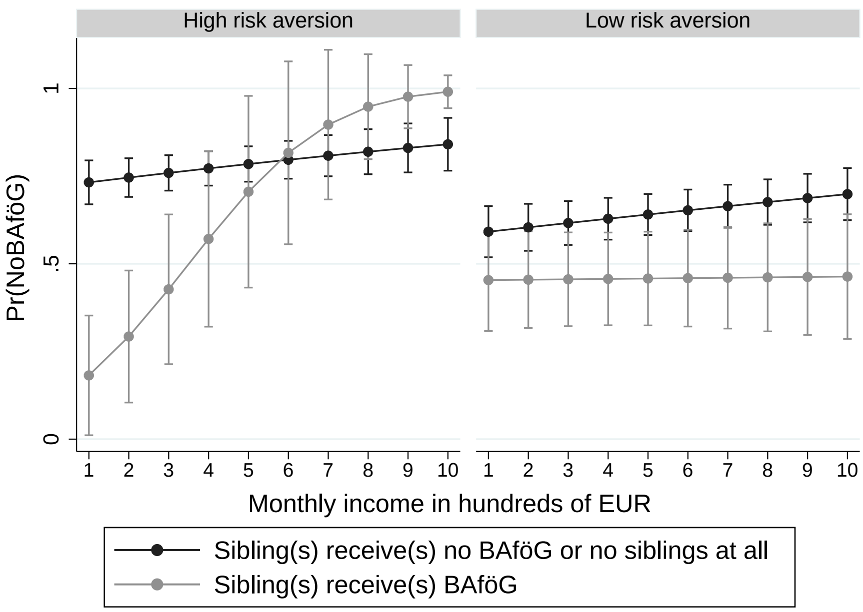
Source: Basic allowances following Herber and Kalinowski (2016).

Table A.4: Definition of Variables

Variable	**Definition**
Dependent	
NoBAföG	= 1 if student does not receive BAföG
Explanatory	
Female	= 1 if student is female
Age	Age in years
East Germany	= 1 if student lives in East Germany
Migration background	= 1 if student has a migration background
Parent(s) has/have uni degree	= 1 if at least one parent has a university degree
Gross parental labor income (100 EUR)	Parental monthly labor income in 100 EUR (gross)
Income (100 EUR)	Student income per month in 100 EUR (gross)
Less risk averse	= 1 if student is willing to take on more risks
Siblings receiving BAföG	= 1 if student has siblings receiving BAföG
Household pays back monthly credit	= 1 if student's family is repaying a monthly credit
Lives with parent(s)	= 1 if student lives with with at least one parent
Simulated aid amount (100 EUR)	Aid amount gained by simulation in 100 EUR

Notes: Income measured on a monthly basis. Siblings variable refers only to the observation period, i.e., when it equals one, the student has siblings receiving BAföG during the observation period. Also, the siblings variable has a zero if the student has no sibling at all or if the student has siblings who do not receive BAföG.

Figure A.1: Predicted probabilities of turning down BAföG depending on student income, information gap and risk aversion



Source: SOEP data 2001 − 2013. *Notes:* Predicted probabilities of students rejecting BAföG depending on their level of income, risk averse behavior and information level of BAföG with 95% confidence intervals (CI's). The dummy variable of students not having any siblings receiving BAföG also contains students who do not have any siblings at all.

Table A.5: Sensitivity analysis with pooled probit

	With simulated aid		Starting in 2007	
	Coeff.	AME	Coeff.	AME
Female	-0.149	-0.043	0.001	0.000
	(0.121)	(0.035)	(0.193)	(0.045)
Age	0.121^{***}	0.035^{***}	0.204^{***}	0.048^{***}
	(0.027)	(0.007)	(0.044)	(0.009)
East	-0.458^{**}	-0.132^{**}	-0.702^{**}	-0.164^{**}
	(0.145)	(0.041)	(0.226)	(0.051)
Migration background	-0.187	-0.054	-0.981^{***}	-0.230^{***}
	(0.160)	(0.046)	(0.239)	(0.051)
Information & Risk				
Parental gross labor	1.000^{***}	0.288^{***}	2.026^{***}	0.474^{***}
	(0.225)	(0.061)	(0.329)	(0.067)
At least one parent has a university degree	-0.048	-0.014	0.049	0.011
	(0.135)	(0.039)	(0.198)	(0.046)
Highly risk averse	-1.450^{**}	0.117^{**}	-2.351^{**}	0.147^{**}
	(0.504)	(0.037)	(0.880)	(0.049)
No sibling receives BAföG	0.061	0.313^{***}	-1.811^{**}	0.034
	(0.310)	(0.058)	(0.661)	(0.086)
Highly risk averse × No sibling receives BAföG	1.848^{***}		2.554^{**}	
	(0.537)		(0.919)	
own income	-0.168	0.022^{**}	-0.361	0.033^{***}
	(0.122)	(0.007)	(0.223)	(0.010)
Highly risk averse × own income	0.537^{**}		0.598^{*}	
	(0.180)		(0.237)	
No sibling receives BAföG × own income	0.225^{+}		0.414^{+}	
	(0.125)		(0.226)	
Highly risk averse × no sibling receives BAföG × own income	-0.500^{**}		-0.372	
	(0.191)		(0.253)	
Debt Aversion				
Household pays back credit	-0.213	-0.061	-0.152	-0.036
	(0.142)	(0.040)	(0.228)	(0.053)
Lives with at least one parent	0.235	0.068	0.453^{*}	0.106^{*}
	(0.158)	(0.045)	(0.201)	(0.046)
Level of benefit				
Simulated aid amount	-0.107^{**}	-0.031^{**}		
	(0.039)	(0.011)		
Year controls	Yes		Yes	
Pseudo R^2	0.204		0.338	
N	988		377	

Source: SOEP data 2001 − 2013. *Notes*: Income and simulated aid amount in 100 EUR. No observations available for 2012 and 2013 (column 2). Robust standard errors in parentheses. Significance given by $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.