Why Do German Students Reject Free Money?

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Abstract

A significant number of German students does not apply for student aid (BAföG) despite eligibility. We build a simple micro-model to derive hypotheses that illustrate the effects of information, income, risk and debt aversion on the decision to abstain from an application. Then, we use GSOEP data to simulate BAföG eligibility and show that in particular risk-averse students with low income benefit from additional information via siblings that already have made use of the aid system. As expected, debt-averse students are more reluctant to apply for aid. Our results suggest that an nontransparent and complicated student aid system disproportionally discourages poor students with little experience with the BAföG system.

JEL classification: I22, I24
Keywords: student aid, inequality, debt aversion

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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 themselves. What remains to be covered are expenses for basic needs and accommodation. Among several options to finance living expenses, students might consider to 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 might 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 admit that without federal aid they would have not been able to study (Middendorff et al., 2017).

However, a sizable number of students who are eligible for federal aid do not apply for it. 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. Out of these formally eligible students only 28% received BAföG (Deutscher Bundestag, 2014). As defined and introduced by Herber and Kalinowski (2016), “formally eligible students" have to be under 30 years of age when starting their first full-time study program. In contrast, there is very little data on the number of “actual eligible students" who have to undergo a means test.

The student survey *Sozialerhebung*, which is published by the Federal Ministry of Education and Research, provides explanations why some of the students did not file a BAföG form in the first place. As the top runner, 76% of students state that 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 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 suggests debt averse behavior, which is especially pronounced for students from lower educational backgrounds, hence, suggesting a positive relationship between the two.

The purpose of this paper is to analyze this repetitive behavior of students of missing out on a potential money source by considering information restrictions, attitude towards risk and debt aversion as the leading sources. The observed student behavior of not taking up federal aid although eligible to, leads first of all to foregone financial resources, consideringIn 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 especially controversial for students in Germany, since it is widely known that upward mobility for German students to tertiary education is still very low in Germany 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) term as the “German exceptionalism". Thus, 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 set up a theoretical model that illustrates the decision of a student whether to apply for BAföG. In the presence of imperfect information about the entitled amount of aid, risk-aversion, and a costly application process, student might find it optimal to refrain from applying for aid. First, the model shows that stronger information frictions give rise to a higher likelihood for non-application. Secondly, the more risk averse a student is, the higher the likelihood to turn down the application. A student with higher risk aversion will react more severely to any changes in the information level as well as changes in student income.

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 not to receive BAföG conditional on being eligible. Despite the fact that the sample is small, we then control for unobserved heterogeneity with a random effects (RE) probit and correlated random effects

(CRE) probit model. We conclude that unobserved heterogeneity exists, hence panel models within this framework are definitely the appropriate model selection. 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. Again, this might suggest that older students mistakenly assume not to be eligible due to their relatively advanced age, as they are not informed enough about the 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. For highly risk averse students with low income who having siblings who receive BAföG (reducing information asymmetries), the predicted probability to reject BAföG is low, whereas it increases with higher income levels. When less information is available (no siblings receiving BAföG or being an only child) only income levels matter, i.e., a higher income level increases the predicted probability to reject BAföG. For low risk averse students the level of information hardly matters. Finally, we find that if a student's family is paying back monthly credit payments the probability to reject BAföG decreases by 6.9% at a 10% significance level in the pooled probit. This effect suggests that students who are more familiar with loans are less debt averse.

As far as we know, this is the first attempt to explain students' reluctant behavior when it comes to applying for BAföG, first by a theoretical model and then continue with some empirical findings. Also, during our research we have not come across any papers that deal with unobserved heterogeneity in the student aid framework. Exclusive panel data for students is rather specific, as individuals only have the student status for a few years until graduating. Hence, the nature of the data set restricts the possibilities for regression analysis. As suggested by Herber and Kalinowski (2016), once panel data is available on a large scale, panel data models to control for an individual's specific traits is an interesting addition to the analysis done so far. Even though the eligible student sample in this thesis can be defined as being rather small, we still find evidence for existing unobserved individual specific traits.

2 Literature Review and Background Information

Financing Studies in Germany

The *Sozialerhebung*, which is published by the Federal Ministry of Education and Research, is representative source to assess the social and economical situation of students in Germany. The average student income was 918 EUR per month, where the most important income source was financial help from parents and student's own income earned by student jobs in 2016. Only 1/4 of all students received BAföG with an average amount of 435 EUR per month. Other minor income sources were, for instance, savings, financial help from relatives and partners, scholarships and student loans such as the KfW (Middendorff et al., 2017).

When introduced in 1970, BAföG was a 100% grant for students and about 45% of all students were receiving it. 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. The share of students who have been supported by BAföG has decreased over time. For instance, in 1979, the age limit was decreased from 35 to 30 (Deutscher Gewerkschaftsbund, 2016). 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. One of the recent reforms in 2001, addressed the repayment of BAföG and capped the total amount of debt at 10,000 EUR. Moreover, child allowances, 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. Then, 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 its latest BAföG report with data from 2012, the federal government states that the total number of students has increased between 2004 and 2012, so did the number of students that are formally eligible for BAföG, however, to a lesser extent. While the reforms of 2001, 2008 and 2010 increased the number of eligible students, they could not stabilize the share of students who actually receive aid in the long-run.

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

Literature

The reluctance of students to take up federal aid, which is analyzed in this framework, is only a specific type of governmental aid. 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 forgo their payments. This reluctance to take up benefits is driven by high information costs, bureaucratically complex forms and stigma effects such as an unemployed individual's negative connotation towards accepting such aid. 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 63.1%, whereas stigma, application cost and social ties affect the decision of a(n) (non-)application. While information frictions, application costs and bureaucratically complex forms might also explain the reluctance of students to apply for aid, there is no evidence that a stigma is attached to receiving student aid.

According to Herber and Kalinowski (2016), BAföG is the only federal student aid program that is administered by the student service departments of higher education institutions. Hence, most students should have at least heard of the possibility to receive federal aid. In addition, they emphasize that there are online calculators that roughly estimate the hypothetical aid amount an individual would receive (Herber and Kalinowski, 2016) as well as the fact that each student is assigned a personal adviser. However, there is growing evidence that information frictions may prevent students from applying for aid. Bettinger et al. (2012) focus on 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 especially 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". According to them, compliance costs are higher for those students who come from low-income families, which is opposed to the goal of especially helping students from

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

these income levels. In contrast, Booij et al. (2012) analyze information restrictions related to Dutch student loans and against their expectation, they cannot show that informing students about loan conditions leads to higher participation rates.
Furthermore, the filing process 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 only to 261 minutes (Bundeskanzleramt und Nationaler Normenontrollrat, 2010).

Ortiz-Nuñez (2014), who 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". 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). 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.

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). 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. According to them, 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. Their data considers U.S. students and distinguishes between individuals living on- and off campus, since students living off-campus receive a part of their aid in cash. This means that 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, for a student without self-control the rejection of a zero-interest loan might still be reasonable as it is a way to restrict overspending behavior. 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.

Herber and Kalinowski (2016) combine the traditional view on non-take up of social benefits such as the duration of benefits and information asymmetries with a different view originating from behavioral economics, i.e., individuals rejecting their aid amount due to the fact that they dislike the idea of bearing additional debt. With a micro-simulation model, they simulate potential BAföG amounts distinguishing between eligible and non-eligible students and restrict their sample to the former mentioned group. They construct the "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, suggesting debt averse behavior. *(An anderer Stelle Zitieren, wenn es um die Bafög-Höhe geht!)Steiner and Wrohlich (2012) find that an increase of BAföG increases the average enrollment rate in higher education.*
(Vielleicht in die Conclusion oder die Introduction, um zu zeigen, wie wichtig das alles ist?)Furthermore, the probability of finishing university successfully increases when students receive BAföG (Glocker, 2011).

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- and debt-aversion, student income, and information frictions.

Setup

First assume for simplicity that there are only two different realizations of student aid, high aid or low aid. Let π_{ij1} be the total income as a student (including student aid, costs of application 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, $\pi_{nht} = \pi_{nlt}$. After graduation, the student enters the labour market and receives income π_{ij2}. 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. Expected utility of a student can be written recursively as

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

where $0 < \beta < 1$ can be interpret as the weight of future utility relative to present utility. 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 this "initial period" 0 ($\pi_{ij0} = 0$). Now consider the utility of a student who applies for student aid before going to university, U_{a0}. With probability p the student receives a high amount of student aid, 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), simplify and reiterate, we obtain the expected utility

$$U_{a0} = p\left[\pi_{ah1}^{1-\rho} + \beta\pi_{ah2}^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} + (1-p)\left[\pi_{al1}^{1-\rho} + \beta\pi_{al2}^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}}. \tag{2}$$

We assume that the exogenous non-aid-dependent income of the student is $\overline{\pi}_1$ and $\overline{\pi}_2$ in the two periods. Thus, the utility of a student who does not apply for student aid is

$$U_{n0} = \left[\overline{\pi}_1^{1-\rho} + \beta\overline{\pi}_2^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}}. \tag{3}$$

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.

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. If this signal would be perfect and would always reveal the correct student aid, that is, $s = a$, the utility of an application would be

$$U_{a0}(s) \quad = \quad \left[(\overline{\pi}_1 - c + s)^{1-\rho} + \beta(\overline{\pi}_2 - s/2)^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} \tag{4}$$

However, information frictions distort the actual signal signal by some distortion e such that

$$s \quad = \quad a - e. \tag{5}$$

We assume that this distortion e is uniformly distributed according to the density function

$$f(e) \quad = \quad \begin{cases} \dfrac{1}{2x} & \text{for } -x \le e < x \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where x can be interpret 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 $a > 2x$, that is sufficiently moderate information frictions, we do not need to consider the restriction that student aid cannot be negative.

In contrast to our simplified approach (2), expected utility now is now aggregated over the different levels of e,

$$U_{a0}(s) \quad = \quad \int_{-x}^{x} \left[(\overline{\pi}_1 - c + s + e)^{1-\rho} + \beta(\overline{\pi}_2 - (s+e)/2)^{1-\rho}\right]^{\frac{1-\alpha}{1-\rho}} \cdot f(e)de \tag{7}$$

Proposition 1 *If $\overline{\pi}_1 + \frac{3}{2}(s + x) < \overline{\pi}_2$, (7) is strictly increasing in s.*

Proof of Proposition 1

$$\begin{aligned} U'_{a0}(s) \quad &= \quad \int_{-x}^{x} \frac{1-\alpha}{1-\rho} u(s)^{\frac{\rho-\alpha}{1-\rho}} \cdot [(1-\rho)(\overline{\pi}_1 - c + s + e)^{-\rho} \cdot 1 + \beta(1-\rho)(\overline{\pi}_2 - (s+e)/2)^{-\rho} \cdot (-1/2)] \cdot f(e)de > 0 \textit{ iff} \\ & \int_{-x}^{x} (\overline{\pi}_1 - c + s + e)^{-\rho} - \frac{1}{2}\beta(\overline{\pi}_2 - (s+e)/2)^{-\rho} de > 0 \end{aligned} \tag{8}$$

Now note that the minuend under the integral is decreasing in e, while the subtrahend is increasing in e. Thus, a sufficient condition for (8) is

$$(\overline{\pi}_1 - c + s + x)^{-\rho} - \frac{1}{2}\beta(\overline{\pi}_2 - (s+x)/2)^{-\rho} \quad > \quad 0 \tag{9}$$

$$\overline{\pi}_1 - c + s + x \quad < \quad \left(\frac{2}{\beta}\right)^{\frac{1}{\rho}} (\overline{\pi}_2 - (s+x)/2) \tag{10}$$

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

$$U_{a0}(s) \geq U_{n0} \tag{11}$$

According to proposition 1, the LHS of (11) 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 can compute the probability that a student with the eligibility for the aid amount a finds it optimal to not apply for student aid.

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

Simulation

We now simulate the decision for students with different levels of risk aversion α, high and low information frictions x, and varying student income $\overline{\pi}_1$ from monthly 100 euros up to 400 euros[3]. 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 $c = 1$.[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 Euros.

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 and translates $\overline{s}$ into probabilities to not apply for student aid

[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.

according to (13). Basic economic theory as well as the simulation give rise to the following two hypotheses.

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

Hypothesis 2 *The probability to not apply for student aid is increasing in the extent of information frictions if students are risk-averse.*

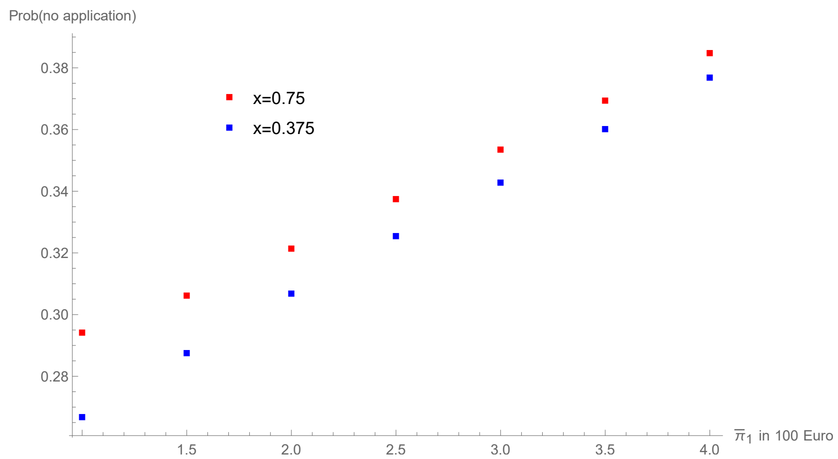


Figure 1: Prob(no application) for student with high risk aversion ($\alpha = 0.9$) and imprecise ($x = 0.75$) or more precise ($x = 0.375$) signal

Figure 2 illustrates the absolute differences of the probability to decline student aid for students with low and high information 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 $\overline{\pi}_1$.*

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.*

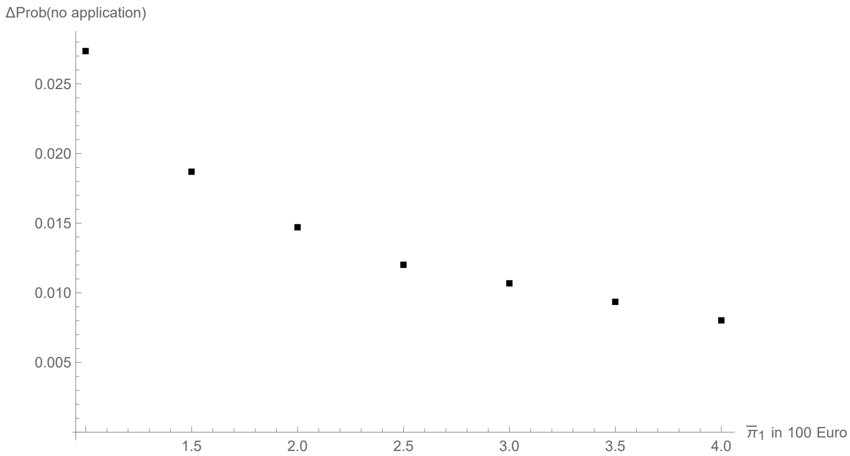


Figure 2: The effect of a better signal on the probability to decline student aid

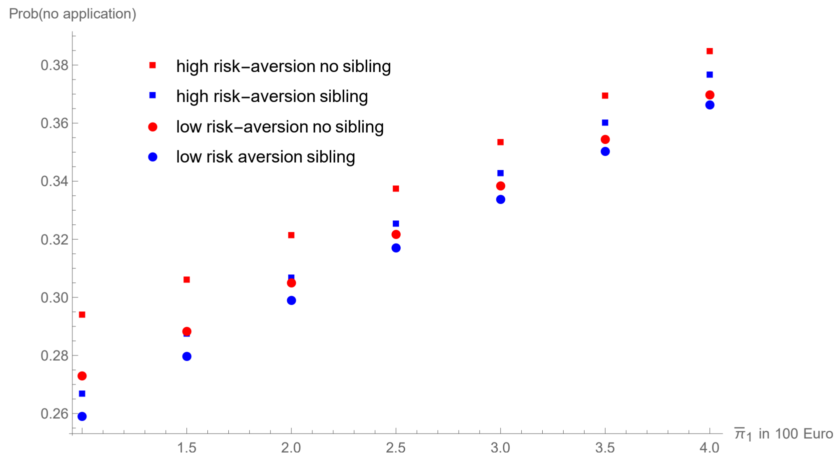


Figure 3: Prob(no application) for students with high risk-aversion ($\alpha = 0.9$) or low risk-aversion ($\alpha = -1$) and imprecise ($x = 0.75$) or more precise ($x = 0.375$) signal

We finally add the student with low risk-aversion to figure 2 and obtain figure 4. 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.*

We used a rather high costs of applying for student aid, $c = 1$. If we interpret these costs as monetary costs (including opportunity costs) and disutility of the application process itself, some might argue this number is a bit exaggregated. However, a successful

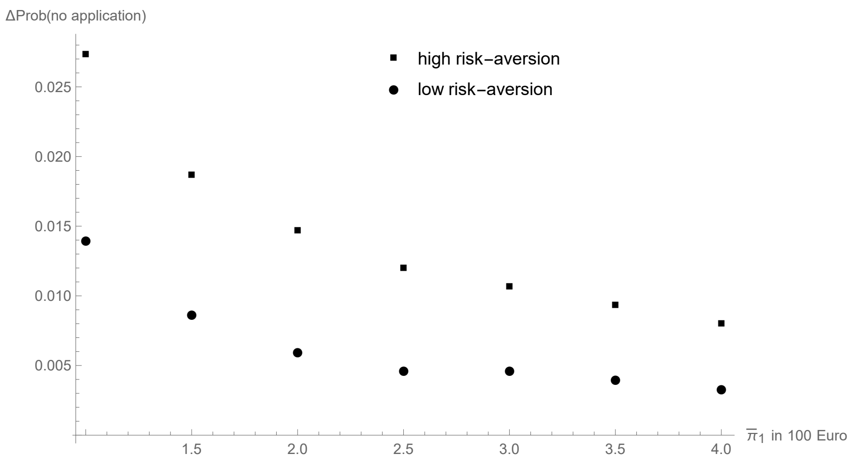


Figure 4: The effect of a better signal on the probability to decline student aid for students with high risk-aversion ($\alpha = 0.9$) or low risk-aversion ($\alpha = -1$)

application for student aid comes with a significant amount of debt for the student. xxx show (SOURCE!) that aversion against this debt may well deter students from applying for student aid, even if this significantly increases the present value of their income streams. There are several way to implement debt aversion into the 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 usually expect that the disutility of owing debt is also increasing in the debt amount and modify (7) 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 proability to apply for student aid.*

4 Empirical Application

4.1 Data and Sample Construction

To analyze the non-take-up of BAföG, we extract data from the German Socio-Economic Panel (GSOEP), which is administered by the German Institute for Economic Research (*DIW Berlin*). The SOEP contains representative micro-data for Germany from 1984 onwards, covering a wide range of topics such as education, employment, income and health. Today, approximately 11,000 households and 30,000 individuals are sampled each year on a voluntary basis.

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 additionally included a second variable in order to distinguish BAföG payments from scholarships. We use the variable that includes both funding schemes because only very few students receive scholarships in Germany and this variable is available for the entire period from $2001-2013$. [5] It is crucial to identify parents, siblings and, if applicable, the partner of an individual. This restriction reduces our sample from 9,170 to 5,892 observations.

We determine eligibility by simulating potential BAföG amounts as the SOEP does not provide this information.[6] The simulation of BAföG payments follows the formula suggested by Steiner and Wrohlich (2012):

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

where students' eligibility for aid amount a, is a function of several variables including the upper limit for BAföG, A. This maximum amount is reduced if the student's main/side job

[5] For $2007-2013$, some students give contradictory answers, which might give rise to a measurement error in the dependent variable.

[6] 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. **We use the approach by Steiner and Wrohlich (2012) in order not to stick too close to the analysis by Herber and Kalinowski (2016).**

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 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 could simulate aid amounts, a. After considering age requirements, 4,057 observations (95.73%) are formally eligible for BAföG payments.[7] 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 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, where they 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.[8]

[7]Formal eligibility requires further information. For instance, 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.

[8]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%.

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.

4.1.1 Choice of Variables

According to our hypotheses from the theoretical model, we expect that a student's non-aid income $\overline{\pi}_1$ (own labour income, transfer from parents) has a positive effect on the probably to not apply for student aid despite eligibility. According to H???, a high own income or transfer from parents makes it easier for a student to cover her expenses via other sources and reduces 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. According to H???, this effect should increase with information frictions.

We determine a student's non-aid income based on different income sources from the SOEP, where we include 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 can bee seen in the Appendix. 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, as the already small sample size would decrease even further. In addition, we assume that missing information does not cause sample selection problems.

Next, we consider both parent's 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. Having a college degree themselves, might enable parents to better 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, since migrant parents might struggle with language barriers that keep them from being informed about potential federal student aid schemes.[9]

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).[10] According to Hypotheses xxx - xxx, we expect that a student's rejection probability is determined by her income level, the amount of information about the BAföG scheme, as well as her attitude towards risk.

Lastly, debt aversion affects a student's choice. The SOEP provides a variable that provides information on whether a student's family is repaying any monthly debt amounts: "Aside

[9] 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 programs. 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.

[10] 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.

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?" We would argue that an individual, who is already familiar with debt, will be more comfortable taking on debt and thus, might be less debt-averse. In contrast, in line with our theory and according to Eckel et al. (2007), not only general behavior towards debt but also the level of current debt determines the degree of debt aversion. People who already have relatively high debt levels would rather circumvent undergoing a further debt contract, even if it would be clearly beneficial to them (Eckel et al., 2007). Unfortunately, we cannot infer the level of a student's or household's dept from the SOEP. However, we use an additional indicator that shows whether the student is living at home during her studies or not. In line with Cadena and Keys (2013), we consider that students living at home choose to do so because they are debt-averse and try to restrict their consumption.[11]

4.1.2 Descriptive Statistics

The sample, which only includes eligible individuals, consists of a total of 1,480 observations with 677 students being observed in an unbalanced panel over 13 years and appearing 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 not to receive it the year after. This persistence suggest 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 might also be driven by unobserved heterogeneity, which will be explained 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 equals 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

[11] 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.

household they live in is currently in debt.[12]

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.

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

[12]Table **??** in the Appendix provides some additional information on coding and also the level of measurement concerning explanatory variables.

suggests a binary response model. Hence, the probability not to apply for BAföG can be modeled as follows:

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

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 is ensured to take on values strictly between zero and one, following the standard normal distribution function $\boldsymbol{\Phi}(.)$. 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. Both (expected) utilities of students are not observable but the actual outcome is. The latent variable can be expressed as

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

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

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

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 one (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 zero 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 zero and variance one. 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.

So far, 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 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 said to be 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 have to 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 allow 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 rather make sure to 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. Even if FE would provide consistent estimates within the probit framework, it could not be used for our purposes, since 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).

4.2.1 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. As a starting point, 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. Still, the percentage of correctly specified values equals 76.84%. As can be seen, the pseudo-R-squared for the pooled model equals 20.3%, which is rather high and proving that the model specification is good in explaining the rejection probability of students.[13] We use personal controls including gender, age, region and migration background. The older a student, the more probable it is that she rejects aidSome 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

[13]McFadden's suggested version of the pseudo R-squared is $R^2_{McF} = 1 - \frac{lnL_{ur}}{lnL_o}$, where lnL_{ur} stands for the log-likelihood of the full and unrestricted estimated model and lnL_0 for the model with only an intercept. When both lnL_{ur} and lnL_0 do not differ much, this implies that adding variables does not change the likelihood of the estimated model, where a small R^2_{McF} results. If however, adding variables to the full model decreases lnL_{ur}, a higher R^2_{McF} is attained (Wooldridge, 2013).

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, such thus parental education levels do not seem to reduce information asymmetries.

In order to determine the relationship between information, income and risk aversion, we add 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 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 is of low risk aversion (base level for risk averse dummy) and an income equal to zero. 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, namely, that for students of high risk aversion, the probability to reject BAföG increases by 12.2% at a significance level of 1%.

Lastly, 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. 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.

Table 4: Estimation Results

	(1) Pooled probit		(2) RE probit		(3) CRE probit	
	Coeff.	AME	Coeff.	AME	Coeff.	AME
Female	-0.130	-0.038	-0.142	-0.026	-0.239	-0.040
	(0.122)	(0.036)	(0.258)	(0.047)	(0.273)	(0.046)
Age	0.113***	0.033***	0.241***	0.044***	0.526***	0.088***
	(0.026)	(0.007)	(0.051)	(0.008)	(0.089)	(0.013)
East	-0.485***	-0.142***	-0.974**	-0.179**	-1.857*	-0.312*
	(0.146)	(0.042)	(0.311)	(0.055)	(0.856)	(0.139)
Migration background	-0.252	-0.073	-0.450	-0.083	-0.159	-0.027
	(0.160)	(0.047)	(0.326)	(0.060)	(0.348)	(0.059)
Information & Risk						
Parental gross labor income (log)	1.179***	0.344***	2.174***	0.400***	1.091	0.183
	(0.214)	(0.057)	(0.412)	(0.065)	(0.899)	(0.150)
Parents have university degree	-0.038	-0.011	0.181	0.033	0.138	0.023
	(0.135)	(0.039)	(0.280)	(0.051)	(0.297)	(0.050)
Highly risk averse	-1.333*	0.122**	-2.461**	0.137**	-2.058*	0.142**
	(0.520)	(0.037)	(0.823)	(0.049)	(0.853)	(0.046)
No sibling receives BAföG	0.103	0.305***	-0.103	0.336***	0.032	0.217*
	(0.307)	(0.059)	(0.524)	(0.065)	(0.545)	(0.084)
Highly risk averse × No sibling receives BAföG	1.740**		3.286***		2.974***	
	(0.553)		(0.847)		(0.875)	
Own income	-0.126	0.025***	-0.303	0.025**	-0.064	0.022*
	(0.116)	(0.007)	(0.236)	(0.009)	(0.259)	(0.010)
Highly risk averse × Own income	0.494**		1.137***		0.953*	
	(0.177)		(0.332)		(0.372)	
No sibling receives BAföG × Own income	0.190		0.416+		0.151	
	(0.120)		(0.242)		(0.258)	
Highly risk averse × No sibling receives BAföG × Own income	-0.456*		-1.112**		-0.919*	
	(0.188)		(0.340)		(0.382)	
Debt Aversion						
Household pays back credit	-0.237+	-0.069+	-0.345	-0.063	-0.038	-0.006
	(0.141)	(0.041)	(0.220)	(0.041)	(0.281)	(0.047)
Lives with at least one parent	0.388**	0.113**	0.617*	0.113*	0.483	0.081
	(0.146)	(0.042)	(0.260)	(0.048)	(0.424)	(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 $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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), stronger information frictions have a highly significant effect (0.1% − 1% level) on the P(NoBAföG). For instance, for a student with a monthly income of 300 EUR, the probability of non-application for a student who is highly risk averse and simultaneously increases by 32.7% at a significance level of 1% if she has no siblings receiving BAföG.

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	

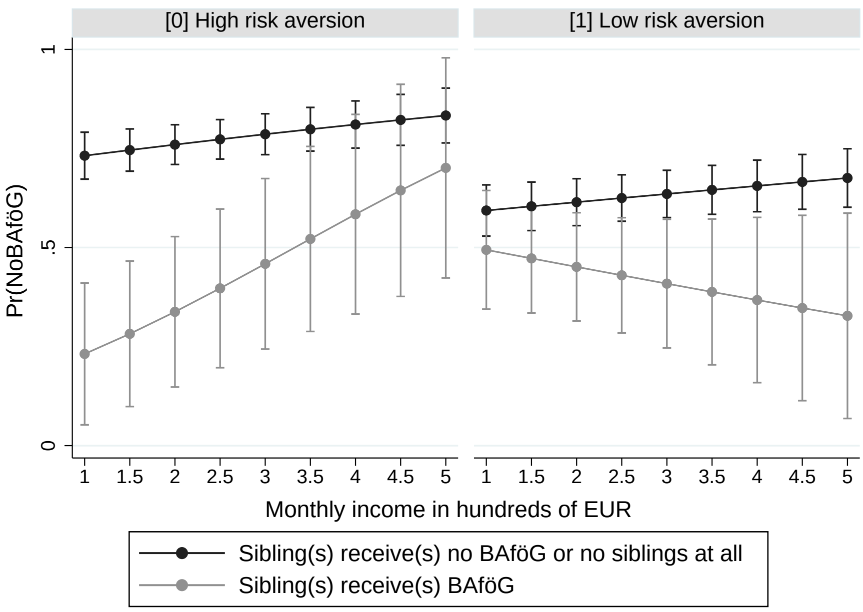
Source: SOEP data 2001 – 2013. *Notes*: AME's from pooled probit. Standard errors in parentheses and significance given by $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 **??** 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. However, the effect is stronger for students with high risk aversion. 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). For more detailed information, see table **??**.

For low risk averse students having siblings who can help them as opposed to not having anyone does not matter as much as for high risk averse students. In line with hypothesis xxx, 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 xxx, a rise in income increases the predicted rejection probability continuously in almost all cases. As an exception, the courve 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, hence leading to possibly biased estimates, which we not worry too much about.

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. The exact probabilities predicted with standard errors and significance levels are recorded in table **??** in the Appendix.

All in all, empirical results for the three-way interaction term seem to undermine the expected effects from theory referring to information restrictions and risk aversion. ***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).*** *Similar to 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).*

If the student belongs to a household which pays back a credit on a monthly basis, the probability to reject BAföG decreases; however, the effect is only significant at 10% significance level. This might be the case because students familiar with debt feel more comfortable to take on even more debt. 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. *For debt aversion, Herber and Kalinowski (2016) use an interaction between impulsivity and impatience of students and also find significant effects (später?).*

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. Further note that AME's mostly differ only in magnitude and *in the sign for the interaction term (REALLY?)*. With respect to personal controls and regional differences there is not much difference in the estimation, the magnitude simply increases. 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? Setting that aside, there is no other remarkable change in the results except for the change of sign for the variable that depicts whether a student's family pays back a credit. *In the CRE model, the AME has a positive sign, as such this is expected if students exhibit debt averse behavior, since they are already in debt and do not want to indebt themselves further. However, the effect is insignificant at any conventional significance level (is this correct?).* 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 small sample might also be the reason for the poor estimation power.

4.2.2 Sensitivity Analysis

The graph A.1 depicts the predicted Pr(NoBAföG) for a different simulation model. We additionally simulate eligibility by not considering own student income as an additional restriction, which necessarily leads to a larger student sample in the end. 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.4 (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.

In the second column, we analyze the same estimation equation with the "'true"' dependent variable only considering the reception of BAföG, which is only available for $2007 - 2013$,reducing our sample size to $N = 377$. This shortcoming already suggests that the estimation might not provide reliable results. Looking at the estimated AME's and comparing them to the pooled probit results in column 1 of table 4 *we find no significant differences to the main model (true?).*

4.2.3 Concerns

The results above 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 reduces from 9,170 to 5,892 observations only 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, we do not expect to have a specific reason for missing parental information leading to a sample selection problem. Eventually, after including all explanatory variables and only keeping those who have information on all relevant independent variables, the sample size in the pooled model equals $N = 988$ and the sample size for the panel models equals $n = 412$, which is rather small. Hence, this raises the question as to how reliable the results are, especially considering the panel models.

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, which leads us to assume that no income was received by the respective income source if no information is available. These two major drawbacks show that it might have been the case that the simulation was not fully able to distinguish between eligible and non-eligible students, which means that the estimation equation might include both eligible and non-eligible students. For instance, the results show that the higher parental income, the more likely students refrain from applying for BAföG (in pooled/RE). Now, keep in mind that the sample might also include ineligible students, explaining the positive effect on P(NoBAföG) if parental income increases.

Some students give contradictory answers to 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. This raises the question as to how reliable students' responses are especially also considering other parts of the questionnaire and as such other explanatory variables that are included into the model. Note that as opposed to a measurement error in the dependent variable, a measurement error in explanatory variables is more severe and would lead to biased estimates if the classical errors-in-variables (CEV) assumption does not hold (Wooldridge, 2010). The measurement error should be uncorrelated to the unobserved explanatory variable. One explanatory variable that possibly suffers from measurement error is own student income. Remember that there is no readily computed total monthly income variable for students in the SOEP. We generate the monthly income considering different income components, whereas students sometimes report their income and sometimes they do not. It is reasonable to assume that they do not know the exact income sources and amounts, which leads to measurement error. Things will only get problematic if the CEV assumption does not hold. However, we do not expect that the error in the income variable is correlated to the true income of the student.

Unfortunately, we were not able to test for other interesting variables, such as social networks or communication with fellow students, leaving aside the question whether the estimates for the siblings variable might be biased. Imagine that students with siblings already receiving BAföG might also have a better network at their university as their siblings introduce them to fellow students right in the beginning of their studies, which allows them to grow a larger social network. Therefore, the estimate concerning siblings might be upward biased partially also containing the effect of fellow students.

5 Conclusion

SHORT Description of our results (max 10 lines).

A policy that aims to subsidize poor students, independent of their attitute towards risk, must take these effects into consideration. The latest 25th BAföG Amendment Act was introduced in 2014 and is again targeted to affect the eligibility status of students. Starting with the winter term 2016/17, for example, the income level of mini-jobs that do not affect the level of funding increased from 400 EUR to 450 EUR per month and BAföG entitlements increased by 7% (Deutsches Studentenwerk, 2017). However, the main result of this thesis addresses the behavior of already eligible individuals. Making more students eligible is only one side to the story. The most important implication for the government and its higher educational policy will be to start off by reducing the existing information gap on the student side. Completely informed students of the BAföG scheme should not be worried about the receipt of BAföG. 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 how the application process looks like, what the repayment scheme looks like and also emphasizing that information centers exist will significantly decrease any information asymmetries. Students would know how and when to file the application and also any misconception about eligibility would be resolved. Even though the 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. As such, future efforts should be targeted towards informing students. However, even if full information among students exists, 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

We start off with the simulation of the maximum aid amounts, A, where table A.1 shows that A was constantly changing throughout the years due to several BAföG reforms in 2001, 2008 and 2010. To compute A, we first need to identify whether students still live "at home" together with at least one parent. For that reason, 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. With the rent that is paid by students we can sort out whether some of them are eligible for an additional high-rent allowance. Note that the rent variable in the sample either shows positive or negative values, however, as in the survey it is only possible to state rent or not, we assume that whenever there is a missing value coded for rent, the student does not pay any. In other words, if information on rent is missing out, we necessarily 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, care insurance payments are received by all students. Some of the students might have children under the age of 10 and hence, they receive additional payments. For that, we collect data on the birth year of their children and sort out 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
+ 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.

Next, p denotes parental (and spousal) income net of taxes and social security contributions as can be seen in table A.2.[14] According to the German Income Tax Law (*Einkommensssteuergesetz (EStG)*), there are seven different income sources considered for the computation of taxable income in Germany. The authors, however, only use four of these income sources, namely labor income, self employment income, income from rent as well as lease and capital income, since these are the only income sources that can be deducted from the SOEP. Furthermore, they add up unemployment benefits and pensions even though these are not part of the taxable income in Germany. They simulate taxes and social security contributions within the tax-benefit model STSM (*Steuer-Transfer-Mikrosimulationsmodell*), since these numbers are not reported at an indivdual level in the SOEP. We use a slightly different 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 $\diamond$
+ Income from rent and lease
+ Capital income (dividends and interest) $\diamond$
+ Pensions
+ Unemployment benefits *(ALG II)*
= Gross income parents and spouse
− Income taxes $\circ$
− Social security contributions $\circ$
$= p$

Source: SOEP data $2001-2013$. *Notes*: $\diamond$ Capital income and income from self-employment are measured on a yearly basis. Hence, we compute the monthly mean. $\circ$ 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

[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.

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 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.

The threshold income, $\bar{p}$, determines whether parental and spousal income are "too high", such that any income levels surpassing this threshold will lower the students' aid entitlements. The threshold incomes or rather allowances are reported in table A.3. 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. Now, keep in mind that 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. High parental incomes might result in negative aid amounts. This, however, does not make any sense and thus, is ruled out.

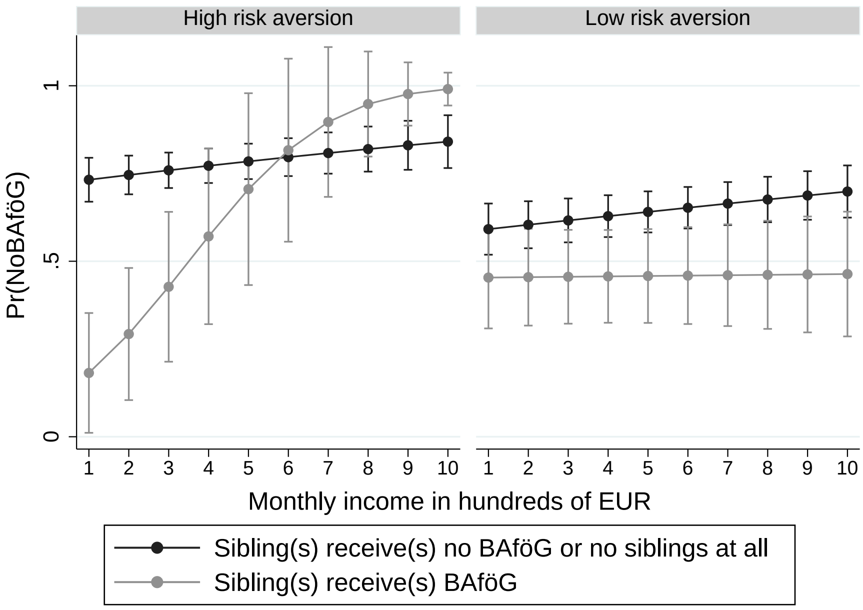
Table A.3: $\bar{p}$ - Threshold income parents/spouse (in EUR/month)

	$2001-2007$	$2008-2009$	$2010-2013$
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 modeled after Herber and Kalinowski (2016).

Empirical results

Figure A.1: 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. The exact probabilities predicted with standard errors and significance levels are recorded in table **??** in the Appendix.

Table A.4: 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 $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.