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REDUCING INEQUALITY BY CORRECTING MISPERCEPTIONS: EXPERIMENTAL EVIDENCE ON STUDENT AID TAKE-UP

Reducing Inequality by Correcting Misperceptions: Experimental Evidence on Student Aid Take-Up*

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Abstract

Financial student aid improves educational outcomes and reduces social inequality, yet many eligible students do not take it up. To examine whether correcting misperceptions increases take-up, I conducted an RCT with 6,225 university students across Germany who were not receiving aid. I find that 63% of students systematically underestimate the financial benefits and overestimate repayment obligations of student aid, and 86% misperceive their eligibility. Providing combined information about the program conditions and individual eligibility significantly corrected misperceptions after six months and increased take-up by 46% after one year. This increase is particularly strong among disadvantaged students. After take-up, students report higher available income while reducing earnings and parental support. These findings suggest that correcting misperceptions can reduce social inequality by alleviating financial constraints among disadvantaged students and their parents.

Keywords: student aid, misperceptions, field experiment, social inequality, BAföG

JEL Codes: C93, D14, D83, D90, H52, I22

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1 Introduction

Students enrolled in higher education often face financial concerns. Evidence across countries shows that the majority of students are in some form of economic distress, such as running out of money by the end of the month (Fletcher et al., 2025), skipping a meal to save money (Brown, 2024), or living at the risk of poverty (Destatis, 2024b). These financial concerns cause higher drop-out rates, increased need for paid work, worse reported health, and slower study pace (e.g. Stinebrickner & Stinebrickner, 2008; Marx & Turner, 2020; Black et al., 2023). This exacerbates social inequalities as these students are more likely to come from socioeconomically disadvantaged families.

To tackle these inequalities, means-tested student aid programs exist to provide help and lower financial concerns. Indeed, receiving student aid leads to better academic performance and financial well-being (see Dynarski, Page & Scott-Clayton, 2023, for an overview). Yet, take-up of financial student aid falls short of eligibility rates. One important but overlooked driver for non-take-up is misperceptions. If eligible students do not take up their entitlement because they misperceive the program's conditions and their own eligibility for aid, this could negatively affect their academic and economic outcomes.

In this paper, I identify important misperceptions that explain low take-up rates and show that correcting them increases take-up. I find that students systematically underestimate the amount of student aid one can receive, underestimate how much parents can earn for a given entitlement, and overestimate the repayment amounts of student aid. Additionally, the majority of eligible students do not think they are eligible for student aid. Then, I show that combined information about aid conditions and eligibility can correct misperceptions in a randomized controlled trial (RCT), and that this correction significantly increases take-up of student aid. This intervention particularly encourages students from low socioeconomic status (SES) families to take up, and take-up significantly reduces financial constraints.

To examine these patterns empirically, I conducted an RCT with 6,225 students who did not receive student aid and were enrolled at universities across Germany. While Germany is similar to the US and other developed countries in that at least 40% of eligible students do not take up student aid (Herber & Kalinowski, 2019), it offers one crucial advantage: a single, need-based federal aid program that is not additionally tied to academic merit, the BAföG[1]. This allows me to focus on one program to determine the role of misperceptions on a national level without considering crowding in or crowding out effects of other need-based programs that students might receive instead (e.g. Park & Scott-Clayton, 2018; Denning, Marx & Turner, 2019). Eligibility and the amount of the entitlement depend on parental income,

[1] Abbreviation for *Bundesausbildungsförderungsgesetz*.

where parents with two children can have an annual household income of up to €120,000 for their children to be eligible for aid. The maximum amount a student can receive per month is €934, decreasing with parental income. Students can receive aid for their standard study period (usually 5 years) and only need to repay 50% of what they receive. This loan is interest-free and capped at €10,010, so student aid debt does not exceed this amount.[2] Based on these conditions, I can determine whether students have systematic misperceptions about the program and whether correcting these misperceptions increases take-up.

The experiment is evaluated over one year. In the initial online survey, I measured perceptions about eligibility and repayment conditions of federal student aid using hypothetical scenarios. Additionally, I asked students if they believed they were eligible for student aid. Calculating the students' entitlement based on their sociodemographic and economic situation, I can measure whether students misperceive their eligibility. At the end of the survey, only the treatment group receives combined information about these conditions *and* their individual entitlement for student aid to resolve potential misperceptions. Using two follow-up surveys to measure misperceptions again and elicit take-up, I can determine the causal effect of the intervention on misperceptions and take-up rates.

I find that students have systematic misperceptions about the conditions of student aid in all three areas captured by the hypothetical scenarios. On average, they (i) underestimate the amount of student aid by €265 (46%) per month, (ii) underestimate the income thresholds for parents by €15,414 (23%) per year, and (iii) overestimate the repayment amounts by €2,827 (42%). In total, 99.2% have at least one of these misperceptions, and 63.1% show all three of these misperceptions simultaneously. This shows that the vast majority of students are systematically pessimistic about student aid. Among the students classified as eligible for student aid, 86% do not believe they are eligible. After six months, students who received the information intervention corrected misperceptions about the conditions overall by 23.8 percentage points (pp) and about eligibility by 16.6 pp. Compared to the control group, this results in a treatment effect of 5.8 pp (32%) and 6.0 pp (57%). The treatment group has a take-up rate of 3.5 pp after one year, resulting in an intervention effect of 1.1 pp (46%) compared to the control group. Estimating the causal effect of correcting misperceptions on take-up reveals that correcting misperceptions altogether increases the likelihood of taking up aid by up to 55.1 pp.

These results mask interesting impacts on social inequality. Using causal random forest estimation (Wager & Athey, 2018; Athey, Tibshirani & Wager, 2019; Athey & Wager, 2019), I find that students from families with relatively low socioeconomic status (SES) and financially disadvantaged students are more likely to take up student aid due to the intervention.

[2]These numbers are based on the student aid conditions in 2023 when the study was conducted.

Additionally, using the panel structure of my data, I find that among eligible students, student aid take-up leads to significantly higher available income but lower work income and less money from parents. This suggests that correcting misperceptions about student aid conditions and individual eligibility by providing combined information can reduce financial constraints on disadvantaged students, their need for paid work, and the burden on their parents. Thus, the intervention potentially tackles social inequality both at the student and family levels.

I contribute to several strands of the literature. First, a large body of literature empirically investigates the take-up of student aid and loans. Receiving financial support from the state improves financial well-being, graduation rates, and later-life earnings (Fack & Grenet, 2015; Bettinger et al., 2019; Denning, Marx & Turner, 2019; Black et al., 2023). Yet, experimental results on increasing the take-up of student aid are mixed. Addressing the complexity of the application process and offering guidance generally increases take-up (Bettinger et al., 2012; Castleman & Page, 2016), though Bird et al. (2021) find no effects. Eliminating the aid uncertainty by offering an unconditional grant also increases take-up (Dynarski et al., 2021). Providing single pieces of information about aid or loans, on the other hand, leads to no changes in take-up (Bettinger et al., 2012; Booij, Leuven & Oosterbeek, 2012; Marx & Turner, 2020; Bird et al., 2021). Yet, an important mechanism of increasing student aid take-up has received little attention: misperceptions. If students do not apply because they hold pessimistic beliefs about their eligibility *and* the student aid conditions, a single piece of information is insufficient. My study is the first to show that students have systematic misperceptions about their eligibility and the conditions of student aid. I contribute by providing causal evidence that resolving these misperceptions simultaneously through a combined information intervention significantly increases aid take-up.

Second, evidence shows that financial constraints during college impair academic performance, health, and increase the need for paid work, while students from low-SES families are more likely to face these constraints (Callender, 2008; Stinebrickner & Stinebrickner, 2008; Triventi, 2014; Marx & Turner, 2020; Black et al., 2023). This creates social inequality within higher education. Reducing these constraints through student loans positively affects educational attainment (Marx & Turner, 2019; Card & Solis, 2020). Additionally, Bhargava et al. (2025) show that applying for student aid improves parents' financial well-being through access to student loans. I contribute to this literature by showing that take-up of student aid improves the financial well-being of students and their parents. Since the effect of the information intervention on take-up is particularly strong among students from low-SES families, it contributes to reducing social inequality in higher education.

Third, I contribute to the literature on the role of misperceptions in decision-making. Empirically, misperceptions have been shown to influence, e.g., educational investment (Jensen, 2010; Kaufmann, 2014; Reuben, Wiswall & Zafar, 2017; Boneva & Rauh, 2018), collective action for recycling (Fuhrmann-Riebel et al., 2024), COVID-19 vaccinations (Bartoš et al., 2022), investment behavior (Haaland & Næss, 2023), insurance demand (Domurat, Menashe & Yin, 2021), and student loan take-up. These studies use different approaches to measure misperceptions: individual or hypothetical expectations without an underlying true value, beliefs about a specific domain, or beliefs at a single point in time to evaluate a treatment effect. I add to this literature by combining approaches. I use different hypothetical scenarios with multiple questions, all of which have an underlying correct answer, along with a Likert-belief elicitation. This allows me to show that students systematically misperceive the conditions of student aid and their eligibility for it. Then, I elicit the same misperception again six months later to show how an information intervention changes misperceptions and how this translates into actual behavior in the form of student aid take-up.

Finally, since Germany does not charge tuition fees, its student aid program is comparable to a social benefit, as the aid is used to cover living expenses. Therefore, it adds to the literature on the non-take-up of general social benefit programs. As with student aid, non-take-up of social benefits despite eligibility is a common problem worldwide, with take-up rates often below 50% (Ko & Moffitt, 2022), exacerbating social inequality and social mobility. The discrepancy between eligibility and take-up primarily stems from the filing process's complexity or high transaction costs, and unawareness about the program (Currie, 2006; Eurofound, 2015). However, there is mixed evidence on which interventions best solve these problems. A reduction of complexity and transaction costs through assistance or simplifications helps in various settings (e.g. Bhargava & Manoli, 2015; Finkelstein & Notowidigdo, 2019; Gray, 2019; Goldin et al., 2022; Castell et al., 2025). Information provision helps in settings where people are unaware of forgoing substantial monetary or service benefits (e.g. Daponte, Sanders & Taylor, 1999; Bhargava & Manoli, 2015; Liebman & Luttmer, 2015; Finkelstein & Notowidigdo, 2019; Cox, Kreisman & Dynarski, 2020; Hemmeter et al., 2025). Yet, it remains unclear from this literature how individual misperceptions about eligibility conditions and own eligibility influence take-up and if correcting misperceptions can increase take-up. I contribute to the literature by identifying these misperceptions on an individual level and demonstrating that correcting them causally increases take-up, thereby reducing social inequality.

The paper is structured as follows. Section 2 provides an overview of the context of student aid in Germany. In section 3, I explain the experimental design and data collection. The intervention effects on misperceptions and take-up are described in section 4. Section 5 concludes the paper.

2 Federal Student Aid in Germany

In Germany, there is only one need-based federal student aid program called the BAföG. While other merit-based scholarships exist, their reach is small, with only 4% of students enrolled in such programs (Kroher et al., 2023). With an annual volume of €2.9 billion and 360,000 students who received on average €663 per month in 2023, the BAföG is by far the largest student aid program in Germany (Destatis, 2024a). Since no other need-based aid exists, I can focus only on the BAföG program to measure misperceptions and take-up of student aid on a national level without considering crowding in or crowding out effects of other need-based programs (e.g. Park & Scott-Clayton, 2018; Denning, Marx & Turner, 2019).

The amount of student aid one receives is split equally into a non-refundable grant and an interest-free loan. Students can receive a maximum of €934 per month, comparable to grants and loans in the US, the UK, and France.[3] As for programs in these countries, students must apply for BAföG every year and pass the means-test. The administration determines how much parents are expected to contribute to the student's living expenses during their time at university. This amount is deducted from the maximum potential aid of €934 to calculate the individual financial aid the respective student is entitled to.[4] Then, if any, the student's monthly salary above €520 is deducted from their entitlement. Students can receive aid for up to the standard duration of their degree program, which is typically five years for a combined bachelor's and master's degree. The application for student aid has no deadline. The only restriction is that one cannot receive student aid for any month before the application. This allows me to analyze how correcting misperceptions increases take-up, as the students who misperceive their eligibility can immediately apply once they correct their misperception.

Student aid in Germany is mainly used for living expenses, as students do not have to pay tuition fees but only an administrative fee of around €600 per year for attending a public university. Public universities host 88% of all students (Destatis, 2023a), and the overall best-ranked universities in Germany are all public. Therefore, the financial barrier to attending university in Germany is low, but students still need to cover their living expenses.

[3]The maximum student aid in Germany is 11,208€ per year. In the US, a combination of a Pell Grant ($7,395) and a Direct Subsidized Loan ($4,750) sums up to $12,145 per year, which equals €11,245 at 1.08€/$ at the time of data collection. In the UK, the Maintenance Loan pays up to £9,978 per year outside London, which equals €11,339 at 0.88€/£ at the time of data collection. This loan has to be repaid in full, however. In France, the main grant *bourse d'enseignement supérieur sur critères sociaux* pays €6,335 and is therefore comparable to the the non-refundable half of the BAföG.

[4]The maximum amount is reduced to €812 if the student is health insured through their parents. In turn, the amount is increased by €160 for each child of the student. The values are based on the program's modalities in 2023/24, when data collection for this study took place.

Due to financial constraints, students from lower SES families have to work more to cover these expenses, which prolongs study time (Triventi, 2014; Avdic & Gartell, 2015) and impairs academic performance (Callender, 2008). Therefore, student aid can be used as an instrument to tackle social inequality even after enrollment, especially since forgoing financial aid results in lower persistence and graduation rates, higher workload during studies, and lower earnings after graduation (persistence: Glocker, 2011; Fack & Grenet, 2015; Castleman & Long, 2016; Bettinger et al., 2019; Denning, 2019; Nguyen, Kramer & Evans, 2019; Murphy & Wyness, 2023; workload: Park & Scott-Clayton, 2018; Denning, 2019; Herber & Kalinowski, 2019; Kofoed, 2022; earnings: Bettinger et al., 2019; Denning, Marx & Turner, 2019).

How much aid students receive severely depends on their parents' income. For the student aid calculation, their income from two years before the application is considered.[5] Parents of applicants with one child can have an annual gross income of up to €85,000, with two children of up to €120,000 until the children are no longer eligible for student aid. The average gross income of couples with at least one child was €91,000 in Germany in 2021, the relevant year for my data collection (Destatis, 2022). Given the magnitude of these thresholds, it is likely that students underestimate them and therefore potentially misperceive their own eligibility for student aid.

Irrespective of the accumulated aid, the loan part of student aid is capped at €10,010, so a receiving student cannot acquire more debt than this. Repayment of the loan starts five years after the standard period of study has ended, so usually when the student has already entered the labor market. Additionally, the student receives a discount of up to 21% if the loan is repaid in one lump sum and, hence, reduces to €7,908. In case the former student's net income is below €1,605 per month[6], the repayment can be deferred. These repayment conditions create room for misperceptions. Students who do not know that only half of the student aid is an interest-free loan and that this is capped at €10,010 might overestimate the potential debt and not take up aid despite eligibility.

Despite its benefits, take-up of student aid is low. At least 40% of eligible students do not take up their entitlement (Herber & Kalinowski, 2019). The problem is not that students apply and do not pass the means-test, but that they do not apply. 80% of the students state that they never applied, from which 63-76% think that their parents' or their spouse's income is too high to be eligible (Kroher et al., 2023). Given the discrepancy between eligibility and take-up, it is very likely that a large share misperceives their eligibility.

[5] The student aid calculation does not consider current income because one has to hand in the income tax receipt of the parents, which is usually only available with a lag of two years. If the parents' current income is smaller, one can request to use this income instead.

[6] Additional allowances apply if one is married and/or has children to take care of.

With the structure and environment of federal student aid in Germany, students likely have misperceptions about the financial value of student aid. That is, they could underestimate the amounts one can receive per month, underestimate parental income thresholds for eligibility, and overestimate the repayment amounts. Additionally, they could misperceive their own eligibility. One can assume that these misperceptions influence take-up. Given these conditions and the absence of other means-tested programs, German student aid provides an ideal setting to analyze the effect of correcting misperceptions on take-up.

3 Experimental Design and Sample

The experimental design, the incentive structure, the variables collected, the information intervention, and the research hypotheses were preregistered at the AEA RCT registry (AEARCTR-0011249[7]) before the data collection started. The preregistration was updated before the follow-up to include additional control variables and a second intervention. Since some students applied but did not receive a decision until the first follow-up, I contacted them for a second follow-up to determine if their application was successful, in order to measure take-up. All additions were preregistered before they were implemented. The study was ethically approved by the Faculty of Management, Economics, and Social Sciences of the University of Cologne ethics committee (230011SR).

3.1 Data Collection

The experiment was conducted over one year to examine if providing combined information on both eligibility for student aid and its conditions corrects misperceptions and increases take-up. The initial survey was collected in May 2023. May was deliberately chosen since the summer term at German universities starts in April. Every eligible student who did not apply for student aid in April has already forgone one month of potential aid. Assuming everyone who planned to apply for the summer term applied in April, data collection started in May with the intention to treat only students who did not intend to apply.

The link to the initial survey was distributed through the general student committees of the 83 public universities in Germany. The committees contacted students with a separate email that exclusively advertised participation in the survey, as part of their monthly newsletter distributed via email, and/or through their Instagram channels. During the survey, students were asked for an email address and for consent to be contacted directly by our survey team for the follow-up.

[7]https://doi.org/10.1257/rct.11249-5.0

At the beginning of the survey, I asked students about their monthly income, as displayed in Figure B.1 in Appendix B. Specifically, students were presented with input fields on how much money they receive from different sources, e.g., their parents, work, scholarships, and federal student aid. If they indicated not to receive any federal student aid, participants were asked if they had applied for this semester or a previous semester. Only students who did not receive student aid and did not apply for this semester were considered for the experiment.

To determine if a student was eligible for federal student aid, I asked participants about their parents' monthly net income in increments of €500. I deliberately asked for net instead of gross income because parents' net income is more tangible to the students and easier for them to answer precisely (Anderson & Holt, 2017). Additionally, I elicited the students' confidence in these income reports for each parent using a slider from 0-100% in increments of 10%. This enables me to measure who knows what their parents earned and who only gave a guess. The elicitation is displayed in Figure B.2 in Appendix B. I also asked participants for their parents' and their own marital status, how many siblings they had, and whether they lived with their parents. This allows me to check who fulfilled the general eligibility conditions and how much student aid they could expect if they applied.

For all participants, I elicited misperceptions about student aid eligibility and repayment conditions. Additionally, students were asked if they believed to be eligible. The measurement of misperceptions is explained in detail in Section 3.2.

After eliciting misperception, students were asked why they did not apply for student aid. I elicited several reasons using a 5-point Likert scale matrix where students were asked to indicate for each reason whether it applied to them or not. The matrix comprised reasons related to not being eligible, such as "My parents have said that their income is too high" or "I have too many assets", but also reasons related to deciding against student aid, such as "I do not want to take on any debt". The complete list of potential reasons is shown in Figure B.3 in Appendix B. The order of the reasons displayed was randomized.

At the end of the survey, a stratified subsample of participants received an information intervention designed to address potential misperceptions, which is explained in detail in Section 3.3.

The follow-up was collected six months later, in November and December 2023, to leave time for the student aid offices to review applications. Unfortunately, six months was insufficient as many students did not have their final application decision in the follow-up. For this reason, students were contacted for another follow-up from July to September 2024. Students were contacted directly via email. In both follow-ups, students started by entering their monthly income from the different sources, such that take-up could be measured through positive student aid amounts. If no student aid was indicated, participants were explicitly asked if they had applied, and if so, whether the application was accepted, pending, or declined.

Additionally, students were asked about the semester they were in, what study field they were enrolled in, at which university they were studying, who mainly handled their finances, if someone in their closest circle received student aid, if they had ever talked to anyone about applying and with whom, and how wealthy they think their parents were compared to other families in the initial survey. In the follow-up, students were asked if they and/or their parents were born in Germany, if their parents were civil servants, and if their parents had a college degree. I also elicited impatience, debt aversion, and impulsivity using 10-point Likert scale questions. The current GPA and enrollment status were elicited in both follow-ups.

Students received lottery tickets for their participation in the survey. Each student received 10 tickets with the chance to win additional tickets based on their answers during the misperception elicitation. In the initial survey, 100 tickets were randomly selected to win €25 each; in each follow-up, 200 tickets were randomly selected to win €50 each. Each student could only be picked once per lottery, so drawing two winning tickets of the same person was ruled out. The increased incentives in the follow-up were already announced to participants in the initial survey to reduce attrition.

3.2 Measuring Misperceptions

I use hypothetical case scenarios of student aid recipients to elicit how well participants perceive the eligibility and repayment conditions of federal student aid. In addition to the scenarios, I elicited the participants' believed individual eligibility for student aid. Each student was asked "Do you think you would get BAföG if you applied for it?" with answers on a 5-point Likert scale ranging from "Definitely Yes" to "Definitely No".

Hypothetical scenarios have successfully been used to measure expectations (e.g. Manski, 2004; Attanasio & Kaufmann, 2014; Boneva & Rauh, 2018; Boneva, Golin & Rauh, 2022). Yet, it also works for perception elicitation, as it enables me to provide participants with all the necessary information to assess a case and state their perception, without only asking for maximum and minimum thresholds of eligibility and repayment conditions. Therefore, I can measure more specifically how well the students can assess the dynamics of student aid and if they have a good perception of its conditions.

I use three different scenarios: One to elicit perceptions of how much financial aid a student can receive per month, one to elicit how much a student's parents can earn for a given amount of student aid, and one to elicit how much a student has to repay. The scenarios were designed in a way that online student aid calculators cannot assess the correct answers without additional information.[8] Additionally, I recorded if participants left the online survey website on each survey page of the misperception elicitation. This allows me to control for further information searches to give better answers. The scenario for the amount of student aid reads as follows:

Anna (22) is a student and lives in a student dormitory. Her father is an employee and had a gross annual income of €60,000 two years ago. Her mother is a housewife and had no income. Anna has free health and long-term care insurance through her parents. She has no assets of her own. Her little sister Sophie (14) is still in school.

Below this scenario, the participants were asked how much student aid Anna receives per month. The information on the housing situation, income, insurance, and siblings is sufficient to assess the correct amount of student aid Anna receives.

For this scenario, two additional questions were asked to alter the case. The participants were told that Anna's mother now instead had an income of €20,000 two years ago and asked how much student aid Anna would receive in this case. Analogously, the participants were asked how much student aid Anna receives if she had assets worth €18,000 instead of no assets. The two questions were presented in a randomized order. Participants received an extra lottery ticket for each correct answer. An answer was considered correct if the entered amount fell within the €200-interval around the actual student aid amount. Recall that €934 is the maximum amount. Table C.1 in Appendix B presents the correct values for each question per scenario. For each of the three questions, students were asked to rate their confidence in their answer using a slider from 0% to 100%. Following the survey guide by Stantcheva (2023), this allows me to elicit both the point estimate of misperceptions and the confidence in potentially wrong answers.

Similarly, the scenario to elicit perceptions on how much a student's parents can earn for a given amount of student aid reads as follows:

Max (20) is in his first semester at university and lives in a shared flat. He has no siblings. His mother is single and works as an employee. His father has broken off contact and cannot be reached. Max has free health and long-term care insurance through his mother. He has no assets of his own. Max receives €360 a month in BAföG.

In this case, students were asked about Max's mother's annual gross income. I deliberately

[8]The student aid calculators are programmed to map complex cases, so they explicitly ask for further information, e.g., the parents' tax burden or the loan amount of student aid. This information is incorporated in the scenarios without explicitly showing it to avoid redundancies.

chose a scenario where only one parent contributes to the student aid calculation. This is easier to answer as participants do not have to consider two incomes. At the same time, I can still measure participants' perceptions of parents' income thresholds for a given student aid entitlement. One more question was asked based on this scenario. I told participants to imagine that Max now has a sister who is also studying and lives in a student dormitory. Students were then asked how much Max's mother earned in this case, given that Max still receives €360 per month. An answer was considered correct if it fell within the €15,000-interval around Max's mother's actual income. As before, students were asked to indicate their level of confidence in their answers.

The third scenario on repayment of the loan reads as follows:

Sara (29) started working after completing her Bachelor's degree. During her 3-year studies, she received €250 in BAföG per month. In total, she received €9,000. Sara repays her BAföG loan in installments.

Here, participants were asked how much Sara has to repay. Two changes were surveyed for the repayment scenario. First, I told students to consider that Sara would repay her loan all at once and asked how much Sara would have to repay in this case. This was asked to measure how well students perceive discounts for repaying the whole loan at once. Second, I told students to imagine that Sara received €500 per month for 5 years instead, so she received €30,000 in total. This change was surveyed to measure if students knew that the student loan is capped at a maximum debt of €10,010. The two additional questions were randomized in order. An answer was considered correct if it fell within the €1,000-interval around the actual repayment amount. Analogously to the other scenarios, students were also asked for their confidence in their answers.

For each correct answer, students received an additional lottery ticket to win the prize of €25 or €50. The same scenarios, albeit with different names, were used in the follow-up data collection to measure how misperceptions at the individual level change over time.

3.3 The Information Intervention

At the end of the initial survey, randomly selected students received information about federal student aid. This is the treatment group. The control group received no information. The information intervention had two screens in the survey. On the first screen, students received information about income thresholds of parents for children's student aid eligibility, the maximum amounts of financial aid one can receive per month, the repayment cap of €10,010 and additional discounts for repaying the loan all at once, and information on age and wealth limits of the applicants. Additionally, links to the official federal student aid website and the application were displayed. Figure B.4 in Appendix B shows this screen.

On the second screen, students eligible for student aid based on their answers received individualized information on the amount of student aid they could receive if they applied. Students who were not eligible or whose entitlement could not be calculated received information on the maximum monthly parental income up to which they would still be eligible. Figure B.5 in Appendix B displays this second screen.

The intervention was stratified at the cohort level, balancing universities by the number of students, federal state, distribution channel of the survey invitation, and university specialization using the minMSE approach (Schneider & Schlather, 2021). Students from the same university, study program, and cohort were always assigned to the same group to minimize spillovers. Appendix A.1 provides a detailed description of the stratification process.

3.4 The Sample

The initial survey was collected from May 2 to May 31, 2023. In total, 22,222 students from all 83 public universities participated and finished the survey. The median participation took approximately 15 minutes. Students with a degree program ineligible for federal student aid, e.g., PhD candidates, and invalid answers during the misperception questions are excluded.[9] Summary statistics for the remaining 21,869 participants are displayed in Table C.2 in Appendix C, split between students who did not apply for student aid yet and those who did. In total, 17,636 consented to be contacted for a follow-up.

Students were contacted for a follow-up in November 2023. Data collection took place from November 2 to December 15. Out of the 17,636 students who consented to be contacted, 12,096 participated in the follow-up, corresponding to a response rate of 68.6%. Median participation took approximately 12 minutes. 6,225 of these did not apply for student aid before the initial survey and indicated no institutional reason for ineligibility.[10] This group is the experimental sample. Comparing the experimental sample to all students who participated in the initial survey that could have been part of the experiment, I do not find evidence for selective attrition, as shown in Table C.3 in Appendix C. The only difference is that participants in both surveys are less likely to think they are eligible for student aid and have

[9] All scenario-answers of student aid amounts above €10,000 per month, income thresholds for parents above €500,000 per year, and repayment amounts above €100,000 were excluded.

[10] Students who are foreigners, study longer than their standard period of study, receive another scholarship, changed their subject, or study something not covered by student aid are institutionally ineligible. In total, 276 non-recipients were excluded for these reasons as they cannot receive student aid.

Table 1: Balance Table of Experimental Sample

	Control Group (N=3265)		Treatment Group (N=2960)		Diff. t-test
Variable	Mean	SD	Mean	SD	p-value
Age	24.284	4.089	24.318	3.786	0.731
Female (=1)	0.621	0.485	0.626	0.484	0.673
Monthly Income in Wave 1 (in €)	1048.478	484.295	1045.080	504.735	0.787
Migration background (=1)	0.206	0.405	0.201	0.401	0.617
Single (=1)	0.966	0.180	0.963	0.190	0.419
Study year	3.654	1.908	3.636	1.902	0.718
Lives with parents (=1)	0.160	0.366	0.164	0.370	0.673
East Germany (=1)	0.179	0.383	0.181	0.385	0.847
Believes to be eligible (=1)	0.087	0.282	0.090	0.287	0.655
Potentially eligible (=1)	0.354	0.478	0.353	0.478	0.928
Response rate	0.673	0.469	0.678	0.467	0.604
Misperception Area (in €)					
Amounts of Student Aid	−266.051	216.423	−262.996	224.420	0.585
Income Thresholds for Parents	−14951.85	24695.91	−15923.55	23028.30	0.108
Repayment Amounts	2887.425	4317.000	2760.481	4148.531	0.237

Notes: The table shows the summary statistics of the experimental sample's control and treatment group participating in the survey and follow-up data collection. The last column shows the p-value corresponding to two-sided t-tests of the means of each group, respectively. Misperceptions are coded as the deviation from the correct value in each elicitation question and averaged per area based on the three hypothetical scenarios used for elicitation. Negative signs indicate that students underestimated the correct values and vice versa.

lower misperceptions regarding income thresholds for parents. Since students who believe they are eligible and who severely underestimate the income thresholds for parents are more likely to apply for student aid between the initial survey and the follow-up, the reported take-up rates can be interpreted as a lower bound.

The experimental sample is similar to a representative student sample without student aid from a nationwide survey among students in Germany from 2021 (Becker et al., 2024). The comparison of the experimental and this representative sample is shown in Table C.4 in Appendix C. The differences are small, which suggests that the experimental sample is a good representation of the German students without aid.

The balance table for the experimental sample is displayed in Table 1. As we can see from the last column, the treatment and control groups are not significantly different from each other in any of the sociodemographic variables or the response rate. Focusing on the last three rows, we see that students have misperceptions about all three student aid conditions. Pooling both groups in Table C.3, students in the experimental sample underestimate the amounts of student aid by €265 (46%), underestimate the income thresholds for parents by

€15,414 (23%), and overestimate the repayment amounts by €2,827 (42%), on average. As the p-values in the last column of Table 1 show, these misperceptions are not significantly different between the control and the treatment group. Thus, the only difference is that one group received additional information about the eligibility and repayment conditions of student aid and their potential entitlement, and the other did not. This allows me to identify the causal effect of this information on misperceptions and take-up rates that were measured as part of the follow-ups.

4 Causal Effects of the Information Intervention

In this section, I test if combined information about aid conditions and eligibility can causally correct misperceptions and, through that, increase the take-up of student aid. For this, I first show how the information intervention changed misperceptions about the student aid conditions and one's own eligibility. Second, I turn to the direct effect of the intervention on student aid take-up. Third, I combine these two channels to identify the causal effect of correcting misperceptions on take-up rates. Finally, I discuss how heterogeneous treatment effects and the impact of take-up on available income affect social inequality in higher education.

4.1 Intervention Effects on Misperceptions

Misperceptions are a potential driver of non-take-up, as they may cause students to question their eligibility, the amount of student aid they can receive, and the repayment amount. As shown in Table 1, the average student underestimates the student aid amount and the income thresholds for parents, and overestimates the repayment amount. This pattern of misperceptions not only appears on average but for the majority of the sample, as the distributions of misperceptions in Figure C.1 of Appendix C show. In fact, 99.2% of the students either underestimate the amounts of student aid, underestimate the income thresholds for parents, or overestimate the repayment amounts. Additionally, 63.1% show all three of these misperceptions simultaneously. Recall that the hypothetical scenarios had incentivized bounds for counting an answer as correct. Using only answers outside these bounds, still 43.5% show all three misperceptions simultaneously. This means that the vast majority of students have a pessimistic view on student aid in all three areas.

To analyze if concise information about these student aid conditions corrects misperceptions, I focus on the effect on these *aid pessimists*. Correcting their misperceptions improves their view of the financial value of student aid, which could cause them to take up student aid. I estimate the following model:

$$MDiff_i = \beta_0 + \beta_1 Int_i + \beta_2(Int_i \times RealOpt_i) + \beta_3 RealOpt_i + \delta_j X_{ij} + \alpha_s + \gamma_u + \epsilon_i \quad (1)$$

The correction of misperceptions is measured as the individual difference in misperceptions, $MDiff_i$, where misperceptions in the follow-up are subtracted from initial misperceptions. Each misperception is measured as a percentage deviation from the correct value in the respective scenario, and averaged per area. Hence, positive values of $MDiff_i$ reflect an improvement in percentage points as misperceptions in the follow-up are smaller than initial misperceptions. Int_i is an indicator equal to 1 for participants who received the information intervention. $RealOpt_i$ is the indicator that shows if an individual is an *aid realist* or *optimist*, so it is equal to 1 for students who overestimate the amounts of student aid, overestimate the income thresholds for parents, and *under*estimate the repayment amounts in the initial survey for at least one question per scenario. This allows me to isolate the treatment effect on correcting misperceptions for aid pessimists, captured by β_1. I control for initial misperceptions per area to measure treatment effects independent of high or low initial misperceptions. Additionally, I control for sociodemographic and control variables from the survey, reasons for non-take-up, and preferences, mentioned in Section 3. Control variables are captured by X_{ij}. Study field and university fixed effects are captured by α_s and γ_u, respectively. The error term is denoted by ϵ_i. Table 2 shows the OLS estimates for the treatment effect β_1. Table C.5 in Appendix C includes the estimates for both aid pessimists (β_1) and realists/optimists (β_2 and β_3). All standard errors are clustered at the study field per university, so one level above the stratification, following Chaisemartin & Ramirez-Cuellar (2024) and Abadie et al. (2022).

The information intervention significantly corrected misperceptions for the aid pessimists. I find significantly positive effects of the intervention on the correction of misperceptions for different areas of student aid in columns 1 and 3 of Table 2, and the total number of questions from the scenarios answered within the incentivized bounds in column 5. Students with a pessimistic view in all questions correct their misperceptions due to the intervention by on average 5.8 pp (32%) more than the control group, as shown in column 4. The results are similar when I use an alternative definition of aid pessimists. Instead of requiring consistently pessimistic answers across all questions in a misperception area, I define pessimists based on their average response. The estimates for β_1 remain significant, as shown in Table C.6 in Appendix C. Thus, the information intervention led to a significant correction of misperceptions of student aid pessimists.

Potential misperceptions about student aid eligibility and repayment conditions might

Table 2: Intervention Effect on Correction of Misperceptions About Aid Conditions

	Correction of Misperceptions about Aid Conditions (in pp)				
	Amounts of Student Aid (1)	Income Thresh. for Parents (2)	Repayment Amounts (3)	Pooled Areas (4)	Number of Correct Answers (5)
Info-Intervention (=1)	0.037***	0.013	0.144***	0.058**	0.040***
	(0.008)	(0.009)	(0.042)	(0.024)	(0.010)
Mean (Control Group)	0.091	0.085	0.254	0.180	0.113
Observations	6,225	6,225	6,225	6,225	6,225
R^2	0.373	0.493	0.391	0.370	0.354
F Statistic	25.323***	41.360***	27.286***	24.966***	23.332***

Notes: The table shows the intervention effects on the correction of misperceptions from the initial to the follow-up survey. Misperceptions are measured as the absolute deviation from the correct values in the elicitation scenarios, divided by these correct values to determine the misperceptions in %. For columns (1)-(3), I use average misperceptions per area, and average misperceptions over all areas for column (4). Column (5) uses the total number of misperceptions, measured as the number of answers to the elicitation scenarios outside the incentivized interval as explained in Section 3.2. The outcome is the correction in misperceptions, calculated as initial minus follow-up misperceptions, such that positive coefficients show a stronger correction of misperceptions in percentage points. The positive coefficients in row 1 show that the intervention significantly reduced misperceptions for the participants who underestimated the financial value of student aid (aid pessimists).
I control for initial misperceptions, all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors at the level of study fields per university are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

also cause students to believe they are not eligible, even though they are. The questions on the sociodemographic and economic background of the students allow me to determine the individual eligibility of students for aid. Additionally, the question on perceived eligibility allows me to measure the extent of misperceptions about own eligibility and how these misperceptions change due to the information intervention.

To measure the intervention effect, I focus on the students who are eligible but think they are not. That is, I first restrict the sample to those with a positive calculated entitlement, the eligible students. To determine eligibility, I use two approaches: Excluding the students' own income, and including it. Recall that the means-test of student aid first only considers parental income to calculate the student's eligibility. Yet, the students' earnings can reduce the amount of student aid they receive after a successful application. Therefore, I distinguish between the more inclusive approach without students' income and the conservative calculation, including students' income. Next, I drop students who answered the Likert scale question on perceived eligibility in the initial survey with “Rather Yes” or “Definitely Yes”, so the students who know they are eligible. The remaining sample consists of students who

Table 3: Intervention Effect on Correction of Misperceptions About Own Eligibility

	Correction of Eligibility Misperceptions (=1)			
	Eligible students: excluding own income		Eligible students: including own income	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.041***	0.030**	0.060***	0.052***
	(0.015)	(0.014)	(0.017)	(0.017)
Mean (Control Group)	0.101	0.101	0.106	0.106
Initial Misperceptions (=1)	0.869	0.869	0.862	0.862
Controls and FEs	No	Yes	No	Yes
Observations	2,361	2,361	1,786	1,786
R^2	0.004	0.118	0.008	0.132
F Statistic	9.208***	2.310***	13.931***	2.005***

Notes: The table shows the intervention effects on the correction of misperceptions about the participants' own eligibility for student aid from the initial to the follow-up survey. Only participants are considered who are classified as eligible for student aid and misperceive this eligibility in the initial survey, so participants that do not believe to be eligible, hence answer the Likert scale question on perceived eligibility with "Rather No", "Definitely No", or "Cannot give a clear answer". The correction of misperceptions is equal to 1 for students who change their eligibility belief or apply for student aid after the initial survey. The fraction of students who initially misperceive their own eligibility is shown in the first row of the table footer. To determine eligibility, the student's sociodemographic and economic situation excluding their own income is used for columns (1) and (2), and including their income for columns (3) and (4). The positive coefficients in row 1 show that the intervention corrected misperceived eligibility significantly by 3 to 6 pp.
I control for all misperceptions from the scenarios, confidence in these answers, sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors at the level of study fields per university are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

are eligible but do not believe they are. Table 3 shows OLS results for the intervention effect on the correction of own eligibility misperceptions, which equals 1 for students who indicate in the follow-up that they believe to be eligible or who applied for student aid after the initial survey.

I find that 86-87% of the eligible students initially do not believe they are eligible for student aid, as shown in the second row of the footer in Table 3. That is, the large majority of eligible students have misperceptions about their eligibility. Yet, information about the conditions of student aid and their potential entitlement helps to resolve these misperceptions. The significant coefficients show that the intervention leads to a 3-6 pp stronger correction of misperceptions compared to the control group. Based on the mean correction of 10.1-10.6% in the control group, as shown in the first row of the table footer, the intervention amplifies this correction by 30-57%. Using all changes in the Likert scale question on perceived eligibility as the outcome instead of the binary variable in Table C.7, I find similar results.

One might argue that students did not accurately report their parents' income, which can lead to distorted eligibility calculations. To test how accurately students report their parents' income, I evaluate the distance between the calculated student aid amount and the actual student aid amount of students who took up aid after the initial survey. The median calculated amount is only €50 smaller than the actual amount, and around a third of the calculated amounts are within €100 around the actual amount. Additionally, for 66-75% of the students, the actual aid amount was larger than the calculated amount. This indicates that students adequately report their parents' income, and the calculated amounts can be considered a lower bound for eligibility.

Overall, the intervention significantly corrected misperceptions of both the general student aid conditions and own eligibility. This raises the question of whether the intervention also increased take-up rates, which is addressed in the next section.

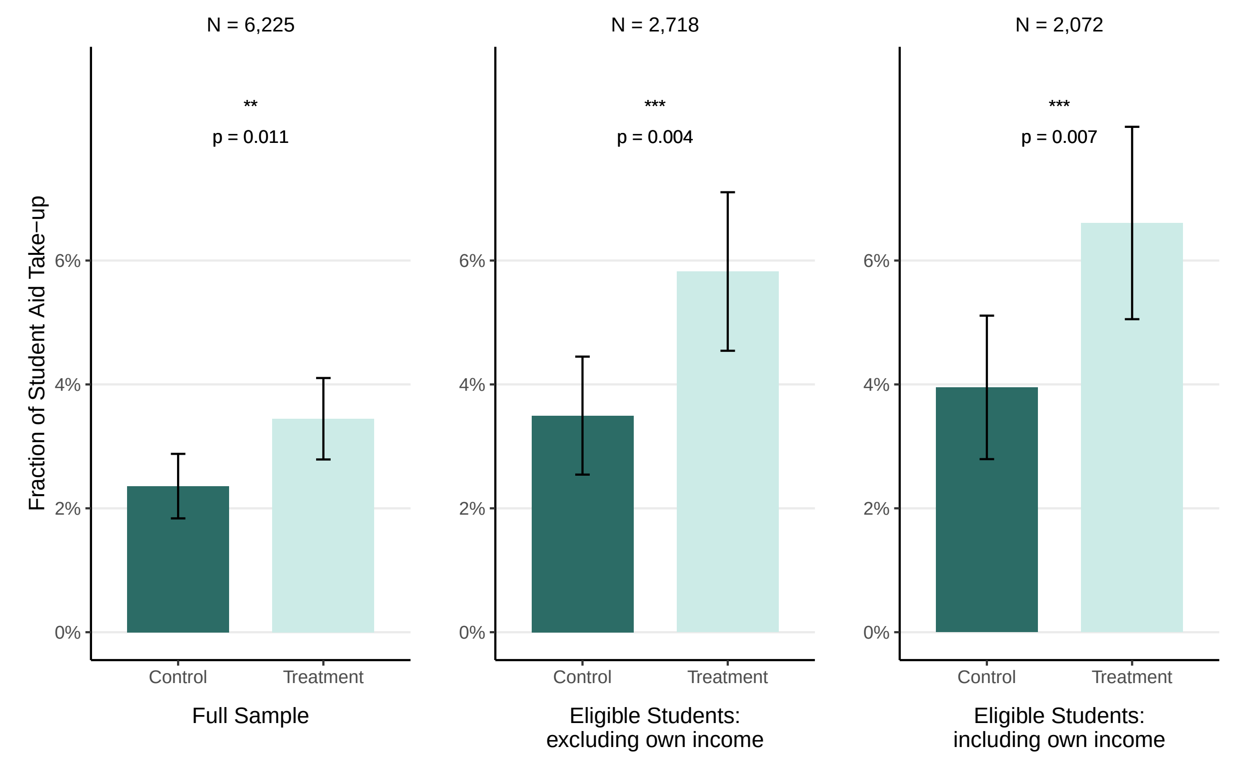
4.2 Intervention Effects on Student Aid Take-Up

To show how the information intervention changed take-up, I compare take-up rates between control and treatment group students after the initial survey. In the two follow-ups, students were asked for their income from student aid. All students who report a positive amount must have taken up student aid after the initial survey, since only students who were not receiving aid and had no pending application at the initial survey are part of the experiment. Additionally, eligible students who indicated a pending application in the first follow-up but did not participate in the second follow-up are considered to have taken up aid. If these students had participated in the second follow-up, they most likely would have indicated a positive student aid amount since they already applied and had a positive calculated entitlement. All results hold when these students are not considered for take-up, reported in Appendix C. The individual eligibility calculation allows me to identify the causal effect of the information intervention on take-up for all students in the sample and among eligible students only.

In Figure 1, I compare the fraction of student aid take-up between the control and treatment groups for the full sample and two restrictions of eligible students. In the middle panel, I exclude their own income to determine eligibility, as this is not part of the means-test. As the student's salary can reduce the amount of student aid they receive per month, however, income is included for determining eligibility in the right panel. Students who learn about their eligibility might reduce working hours to receive their full student aid entitlement. Therefore, both cases to determine individual eligibility are depicted.

The treatment group has a significantly higher take-up rate in all three panels than the

Figure 1: Intervention Effect on Student Aid Take-up for Full Sample and Eligible Students



Notes: The figure shows the increase in the fraction of student aid take-up for the control and treatment groups. In the left panel, the full sample is used to calculate the fractions. In the middle and right panel, only the eligible students, excluding and including their own income when determining eligibility, are displayed. The sample size and p-values of the difference between the two groups are reported above the bars.

control group. While 2.4% of the control group in the full sample take up student aid, 3.5% in the treatment group do. The information intervention, therefore, led to a significant 1.1 pp increase in take-up, corresponding to an effect size of 46%. While students in the control group receive €506 per month, on average, students in the treatment group receive €531 after take-up. This suggests that more entitled students react to the intervention. In line with this, I find stronger intervention effects among eligible students. In the middle panel, we see an increase from 3.5% to 5.8%, and in the right panel from 4.0% to 6.6%, corresponding to effect sizes of 67% each. This suggests that the intervention effect was driven by students whom I classify as eligible for student aid. Regression results for the full sample are presented in Tables C.8 and C.9, and for the eligible students in Tables C.10 and C.11 of Appendix C. Probit estimations are shown in Appendix D as robustness checks.[11]

[11] As preregistered, I also analyze the effect of a second, cross-randomized intervention to test if information about eligibility alone increases take-up. The intervention was part of an email sent to all participants where 200 students of each the control and treatment group received an extra paragraph informing only about their eligibility for student aid. Due to a lack of power, I do not find significant effects. OLS regression results are reported in Table C.12.

Most students who receive student aid take up their entitlement at the beginning of their studies. Only 1.4% of students take up student aid after their first semester.[12] Since the students in the experimental sample are already enrolled, the intervention effect can be interpreted as increasing this fraction. With a 1.1 pp increase, the intervention nearly doubles this fraction. Yet, 2.1% of the control group also took up aid without the intervention, which suggests that I measure a lower bound.

Even with this lower bound, the economic significance is already quite large. Assuming that students would receive the current average student aid of €663 per month after scaling up, a 1.1 pp increase in take-up would be equivalent to €180 million more student aid per year. A comprehensive cost-benefit analysis shows that the governmental investment in student aid yields a return of up to 271% in income tax revenue, assuming that student aid benefits study pace, graduation rates, and post-college income, as shown in previous studies (Fack & Grenet, 2015; Bettinger et al., 2019; Denning, Marx & Turner, 2019). Even minor increases of 12.2-14.7% on the share of student aid recipients who pursue a master's degree after completing their bachelor's alone result in positive returns for the state. This highlights that the government benefits from increased student aid take-up through income tax revenues in the long term. The cost-benefit analysis is detailed in Appendix A.4.

One might argue that spillovers could have biased the intervention effect. Since the treatment was carefully stratified and participants were spread across the country, spillovers are unlikely to be a concern. Yet, some circumstances could facilitate spillovers, such as the number of participants at a single university or university size. That is, at universities with a large number of participants, it is more likely to know someone who also participated but was assigned to the opposite group. To test this, I compare the overall intervention effect of 1.1 pp to average intervention effects at the universities where spillovers could have been facilitated, such as universities with many participants. The results are reported in Table C.13. I do not find any significant differences between university-level effects and the overall effect. This supports that spillovers are unlikely to have biased the intervention effect.

4.3 Correcting Misperceptions to Increase Take-Up

Until now, we have seen that the intervention effectively corrects misperceptions and increases take-up. Yet, we do not know the causal effect of correcting misperceptions on increasing take-up. To analyze this, I can make use of the experimental design and estimate the local average treatment effect (LATE) by using the intervention as an instrument (Im-

[12]The national take-up rate is 11% (Deutscher Bundestag, 2021). In my survey, only 12.5% of the students who receive student aid at some point take up aid after their first semester. Taken together, only 1.4% of all students take up aid after the first semester.

bens & Angrist, 1994; Angrist, Imbens & Rubin, 1996). All assumptions to estimate the LATE are fulfilled. A detailed discussion is provided in Appendix A.3.

The LATE yields the causal effect of correcting misperceptions on take-up for the compliers, i.e., the students whose misperceptions are correctable through information. As first stage, I estimate the treatment effect on correcting misperceptions and use the resulting estimates for the effect on take-up. Equations 2 and 3 show the two-stage least squares model (2SLS).

$$MDiff_i = \beta_0 + \beta_1 Int_i + \delta_j X_{ij} + \alpha_s + \gamma_u + \epsilon_i \quad (2)$$

$$Takeup_i = \pi_0 + \pi_1 \widehat{MDiff}_i + \mu_j X_{ij} + \alpha_s + \gamma_u + \eta_i \quad (3)$$

In the first stage, $MDiff_i$ is the correction of misperceptions from the initial to the follow-up survey, and Int_i is the intervention indicator. In the second stage, $Takeup_i$ is the indicator for take-up as the dependent variable, and $\widehat{MDiff}_i$ is the estimate for the correction of misperceptions from the first stage as the explanatory variable. I include initial misperceptions, sociodemographic and control variables from the survey, reasons for non-take-up, and preferences mentioned in Section 3, which are captured by X_{ij}. Study field and university fixed effects are included with α_s and γ_u, respectively. The error terms are given by ϵ_i and η_i. Results for the 2SLS-estimator are shown in Table 4 for different misperception specifications.

I analyze the effect of misperceptions about own eligibility, using only an indicator equal to 1 for students that correct their misperceived eligibility in columns 1 and 3, as well as using changes in the Likert scale to identify the correction in columns 2 and 4. The first and the second two columns again differ in how the student's eligibility is calculated: excluding the student's income or not. The last two columns show the 2SLS-coefficient for correcting misperceptions about student aid eligibility and repayment conditions, pooling over all scenario-questions in column 5, and using the total number of answers within the incentivized bounds in column 6. The coefficients in the first row indicate that correcting misperceptions causally increases student aid take-up. All coefficients are significantly positive, ranging from 0.384 to 0.551. This means that a 1 pp reduction in misperceptions raises the likelihood of take-up by 0.39 to 0.55 pp. Fully correcting misperceptions, so by 100 pp, can increase take-up among compliers by up to 55.1 percentage points. The significant effects across all six specifications show that correcting misperceptions causally increases take-up rates.[13]

One might argue that the instrument is weak as the first-stage F-statistic is below 10 in

[13] I find similar significances when I use a probit model as second stage, as shown in Table D.4.

Table 4: Causal Effect of Correcting Misperceptions on Student Aid Take-Up (LATE)

	Take-Up of Student Aid (=1)					
	Eligible Students: excl. own income		Eligible Students: incl. own income		Scenarios	
	Binary	*Likert*	*Binary*	*Likert*	*Pooled*	*Total*
	(1)	(2)	(3)	(4)	(5)	(6)
Correction of Misperceptions	0.551**	0.535**	0.398***	0.444***	0.384**	0.424**
(=1 / in pp)	(0.242)	(0.210)	(0.148)	(0.166)	(0.166)	(0.172)
Observations	2,361	2,361	1,786	1,786	6,225	6,225
1st stage F Statistic	4.330	6.487	9.642	11.597	14.475	24.503

Notes: The table shows results from 2SLS estimation of the correction of misperceptions from the initial to the follow-up survey on student aid take-up with the information intervention as an instrument. The correction of misperceptions is measured as the difference between misperceptions in the initial and the follow-up survey, where columns (1)-(4) use misperceptions about the participant's own eligibility and columns (5)-(6) about the financial value of student aid based on answers to the elicitation scenarios. For columns (1) and (2), the participants' eligibility is calculated excluding their own income. The correction of misperceptions is measured using a binary variable or all changes in the Likert scale, respectively. Analogously, columns (3) and (4) include the student's income for the eligibility calculation. For column (5), all percentage deviations from the correct values of the scenario elicitation questions are pooled. For column (6), the total number of answers outside the incentivized interval around the correct value is used as misperception. The coefficients indicate the percentage point increase in take-up resulting from correcting misperceptions by 1 pp for the compliers, i.e., students whose misperceptions can be reduced through information.
I control for all initial misperceptions from the scenarios, confidence in these answers, sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects in both stages. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

the first three columns. Yet, the persistently positive effects of similar magnitude for the remaining three columns with higher F-statistics show that even if the instrument is weak, there is evidence for a causal effect of correcting misperceptions on take-up.

In line with this, I find evidence that students took up student aid because they learned about their forgone entitlement. As part of the follow-up, I asked students from the treatment group who took up student aid what part of the information intervention led them to apply. The share of answers is shown in Table C.15. With 90.5%, most students said the information that they could possibly expect a positive aid amount was the driver for their application. This underlines that the intervention helped students to realize they are eligible for student aid, thereby correcting misperceptions about their eligibility. Additionally, more than half of the students answered that the monthly student aid amount and parental income information led them to apply. This indicates that the combination of addressing misperceptions about the student aid conditions and own eligibility led to take-up.

Alternative mechanisms for how the information intervention increased take-up are unawareness and salience of the student aid program. Students could be unaware of student aid before the intervention. This is unlikely to be the case here. Recall that the BAföG program is the only means-tested and overall most prominent student aid program in Germany. The term "BAföG" is so prominent that it is commonly used as a synonym for federal student aid. In this survey, only 4 out of 6,225 participants indicated they had not heard about the program before. What percentage of students reported each reason for non-take-up is shown in Table C.14. Despite being aware of the student aid program's existence, the intervention could have increased its salience. Since the survey focuses on student aid and the misperception scenarios specifically ask about BAföG, the salience of the program has already increased for the control group. The intervention, however, specifically informs about the program's conditions and own eligibility. Thus, the information provided goes beyond increasing salience and tackles potential misperceptions.

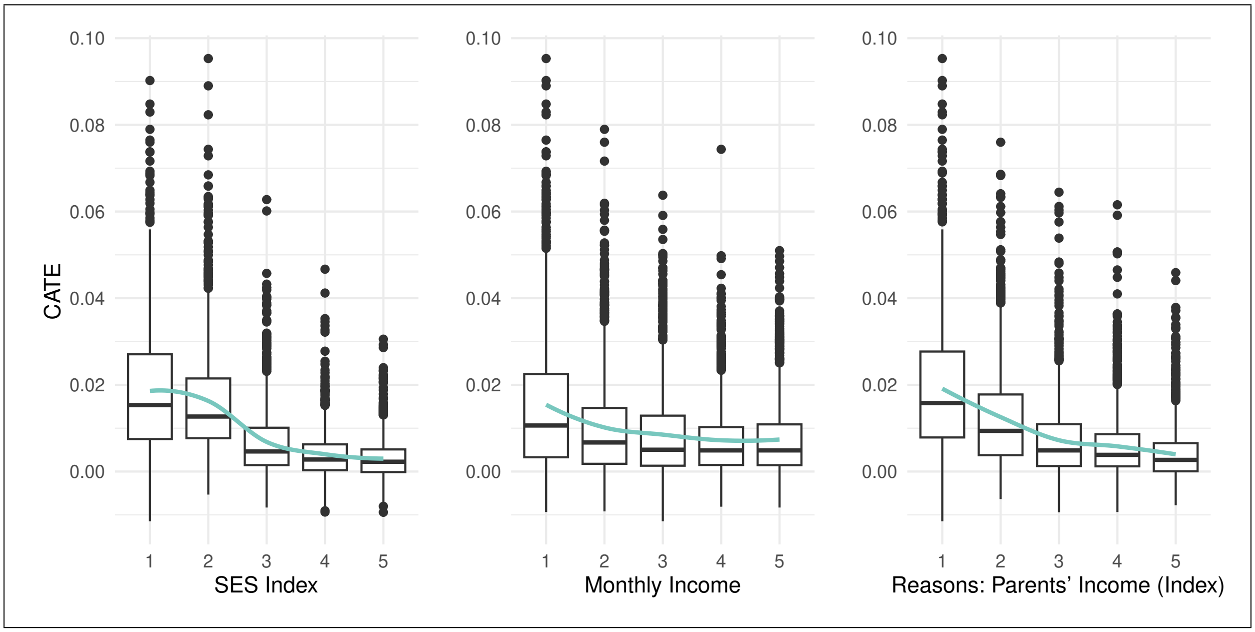
Overall, the results show that correcting misperceptions about eligibility and repayment conditions *and* individual eligibility causally increases take-up. This correction is the driving mechanism behind the intervention effect on take-up. Yet, it is unclear which students particularly benefited from the information intervention to take up student aid and how social inequality is affected. For this, I will analyze the heterogeneity of the intervention effects and the effect of take-up on available income next.

4.4 Effects on Social Inequality

To analyze which students are particularly affected by the intervention and took up student aid, I use the causal random forest algorithm (Wager & Athey, 2018; Athey & Wager, 2019), which has gained increasing attention for analyzing heterogeneous treatment effects (e.g. Davis & Heller, 2017; Serra-Garcia & Szech, 2023). Before I apply the algorithm, I use principal component analysis (PCA) to create an index for socioeconomic status (SES). The index comprises parents' income with the highest weight, followed by the belief that parents are relatively poor compared to other families, migration background, parents' education, and if one parent has already died. A higher SES-Index corresponds to a higher SES.

Analogously, I use PCA as a dimension reduction technique to comprise different reasons for non-take-up of student aid that students indicated on a 5-point Likert scale. The PCA yields three components. The first captures application or student aid program-related reasons, such as application complexity or debt aversion. The second captures reasons related to their parents' income being too high for eligibility and receiving sufficient financial support from their parents. The third captures reasons related to the student's own financial situation, such as earning too much or having too many assets. Higher values in these

Figure 2: Conditional Average Treatment Effects of Variable Quintiles



Notes: The figure shows the conditional average treatment effects from causal forest estimation for the three most important variables to explain the heterogeneity of the intervention effects following the causal forest algorithm. Boxplots for the variable quintiles are displayed. The mean CATEs are connected with a fitted line.

components correspond to a higher agreement with the respective reasons why one has not applied for student aid. The SES-Index and the three components of non-take-up reasons are used for the causal forest analysis instead of the variables they comprise. A detailed description of the PCA and the indices is provided in Appendix A.2.

Following Athey & Wager's (2019) algorithm, I first train a pilot causal forest on all variables, including misperceptions, the SES-Index, other sociodemographic characteristics, and the reasons for non-take-up. Then, I train a second forest on only the variables that received above-average variable importance.[14] Both causal forests used clustering on the study field per university level, one level above the strata from the treatment assignment, as done throughout my analysis. Last, following the algorithm, I use the second forest to estimate out-of-bag predictions. That is, I estimate the conditional average treatment effects (CATE) for each observation within the sample using only trees that did not use the respective observation for the prediction. The CATEs from these predictions for the quintiles of the three most important variables for heterogeneity based on the causal forest are presented in Figure 2.

The CATEs indicate that students with higher financial constraints and more disadvan-

[14]Variables have a higher variable importance if they are included in more sample splits within the trees of the causal forest to reduce the heterogeneity of the subsamples.

taged backgrounds react more strongly to the intervention. Starting from the left panel, the most important variable is the SES-Index. We can see that especially students with low SES have high CATEs. In line with this, students with low income show higher CATEs in the middle panel. Additionally, we see in the right panel that students with a low index of reasons related to parental income react strongly to the treatment. Recall that a low index means these students do not believe their parents' income is too high for eligibility, nor do they receive sufficient financial support from their parents. This suggests that financially disadvantaged students, in particular, benefit from the intervention and take up student aid.

Analyzing these heterogeneities not only for the predicted CATEs but also the true intervention effects, I estimate the interaction effects of these three variables with the intervention, controlling for the individual student aid entitlement in an OLS regression. Results are presented in Table C.16 in Appendix C.

The estimation results corroborate the findings from the causal forest predictions. As a result of the intervention, students from the lower SES quintiles, lower income, and who rank low on the index of reasons for non-take-up related to parents' income are more likely to take up student aid, independent of their entitlement. Additionally, the entire intervention effect is explained by these groups as the treatment coefficient for the high-quintiles becomes close to zero and insignificant. Including all interaction terms and variables, the effects of low SES and income stay significant. Similar patterns are found for the eligible students and using the conservative take-up definition, reported in Tables C.17 to C.21.[15] This shows that especially students in need of financial support react to the information in the intervention and take up student aid.

To test whether the take-up of student aid reduces financial concerns, I use the panel structure of the survey to examine income changes over time. I focus on students who are eligible for student aid and compare those who took up aid with those who did not. The regression results are presented in Table 5. Since aid is only taken up after the initial survey, the first row captures initial income differences between recipients and non-recipients. Consistent with the heterogeneous intervention effects, aid recipients initially have 16% lower total income, as well as lower income from work and parental support. Next, the coefficients for the follow-up dummy reflect income changes among non-recipients over time. Over the one-year evaluation period, non-recipients experience a significant increase in total income and earnings from work, alongside a reduction in parental support. The interaction term's coefficients show the additional income change of aid recipients after take-up. After one year, in the second follow-up, recipients' total income increases by 11.8 pp more than that of non-recipients, almost closing the initial income gap. At the same time, aid recipients reduce

[15] The respective probit estimations are reported in Tables D.6 to D.11.

Table 5: Relative Changes in Income of Eligible Students over Time

	Relative Income (in %)		
	Total	from Work	from Parents
	(1)	(2)	(3)
Take-Up (=1)	-0.160^{***}	-0.236^{**}	-0.150^{**}
	(0.050)	(0.111)	(0.060)
Follow-up 2 (=1)	0.126^{***}	0.350^{***}	-0.023^{*}
	(0.011)	(0.027)	(0.014)
Take-Up (=1) X Follow-up 2 (=1)	0.118^{**}	-0.446^{***}	-0.160^{***}
	(0.053)	(0.124)	(0.053)
Reference Income in €	1024.79	379.87	497.67
Observations	3,110	3,170	3,170
R^2	0.140	0.150	0.205
F Statistic	500.508^{***}	554.303^{***}	812.266^{***}

Notes: The table shows results from an OLS panel regression with individual-level random effects of relative income over time for students who are classified as eligible for student aid in the initial survey excluding their income. Relative Income is measured as the absolute income participants report in each survey divided by the average income in the initial survey of participants who do not take up student aid to measure the relative change compared to this reference group. *Follow-up 2* is equal to 1 for the observations in this period, capturing the time change. *Take-Up* is 1 for all participants who take up student aid after the initial survey. I control for sociodemographic characteristics. Robust standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

earnings from work, as the interaction offsets the time change of non-recipients in column 2. Recipients also reduce parental support by 16 pp more than non-recipients, as shown by the interaction effect in column 3. These results persist when I include the first follow-up and use the alternative eligibility classification, as shown in Table C.22 in Appendix C. Overall, aid recipients are financially better off while substituting income from work and their parents with newly gained student aid. As these students come from financially disadvantaged families, this suggests that take-up reduces not only the students' financial concerns by increasing their total income, but also the strain on parents, who do not have to support their children as much.

The intervention contributes to reducing social inequality in higher education, which is the purpose of student aid. By correcting misperceptions, it helps disadvantaged students to realize their eligibility for student aid and alleviates financial distress through take-up. Since students have a lower workload after take-up, they potentially have favorable downstream benefits such as a shorter study time and better grades, as suggested in earlier work (Callender, 2008; Triventi, 2014; Avdic & Gartell, 2015; Bettinger et al., 2019; Black et al., 2023). Additionally, the reduction in parental support indicates that the families also benefit from take-up, in line with Bhargava et al. (2025). Since the intervention is particularly effective for students from low-SES backgrounds, it eases the financial burden on the whole family as the student requires less support. As a result, it addresses social inequality at both the student and household levels.

5 Conclusion

Student aid aims to reduce social inequality in higher education. Yet, many students do not take up the financial student aid to which they are entitled, resulting in higher dropout rates, higher levels of paid work during their studies, and lower earnings later in life (see Dynarski, Page & Scott-Clayton, 2023, for an overview). One main reason why students do not take up student aid could be that misperceptions about the program lead them to underestimate its financial value and question their eligibility. In fact, I show that students systematically underestimate the financial value of student aid, but that combined information about the program conditions and eligibility corrects misperceptions and increases take-up, particularly among financially disadvantaged students.

In an experiment with 6,225 non-recipients of student aid, I use hypothetical scenarios combined with a Likert-scale question to elicit misperceptions about the student aid conditions and eligibility. Given that Germany has only one federal student aid program, I can focus on this program alone to measure misperceptions and take-up of student aid on a national level. On average, 99.2% of the students underestimate how much financial aid one can receive per month, how much parents can earn for a given entitlement, or overestimate how much must be repaid. Additionally, 86% of the students who are entitled to student aid based on their sociodemographic and economic situation believe they are not eligible.

Providing combined information about these conditions and individual entitlement to a stratified subset of students leads to a significant correction of misperceptions six months later. Additionally, the intervention increased student aid take-up by 1.1 pp (47%) for all students and up to 2.7 pp (68%) for eligible students. The mechanism behind this effect is the correction of misperceptions. Estimating the causal effect of this channel reveals that correcting misperceptions altogether increases take-up by up to 55 pp.

Heterogeneity analysis reveals that the intervention was particularly effective among students from lower socioeconomic status and with lower income. Additionally, student aid take-up is associated with higher total income one year after the intervention, but lower income from work and lower financial support from parents. This suggests that take-up not only reduces the students' financial constraints but also relieves their parents. As a consequence, the intervention tackles social inequality at the student and the family levels.

Using national statistics on student aid, a cost-benefit analysis highlights the potential impact of the intervention. Scaling up the provision of information on student aid conditions and individual entitlement to all non-recipients could increase the total aid available to students by €180 million per year. Over the course of recipients' working lives, this investment could generate an income tax return for the state of up to 271 percent.

The findings show that correcting misperceptions through combined information about student aid conditions and individual entitlement is a powerful mechanism to increase take-up. The intervention could be a feasible and scalable policy to tackle social inequality in higher education. Since the intervention particularly increases aid uptake among disadvantaged students, the results suggest that correcting students' misperceptions could help them take up their entitlement and achieve better educational and economic outcomes by alleviating financial constraints.

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Appendix A: Additional Technical Explanations

A.1 Stratification of the Information Intervention

The information intervention was stratified at the cohort level. That is, I created a list with all public universities in Germany, how many students are enrolled there, in which federal state they are, if it is a general university or has a technical or other specialization, and what distributional channels for inviting participants was agreed upon with their respective general student committee. Next, I used the minMSE approach (Schneider & Schlather, 2021) to match universities and create two balanced groups considering the mentioned information.

Additionally, I created two groups out of the 18 study fields in Germany[16] that each comprise approximately 50% of the student population while considering that some fields have overlapping courses. For example, mechanical and electrical engineering are selected into the same group due to their content-related overlap. The control and treatment groups are constructed based on the university and study field groups. In the first university group, the first cohort[17] of the first study field group is assigned to treatment while the second cohort[18] is not. Analogously, for the second university group, the first cohort of the first study field group is assigned to control, while the second cohort is not, and so forth for each cohort of each study field and university. Therefore, spillovers are minimized since students from the same cohort of a given study field and university are assigned to the same group. At the same time, treatment is still distributed balancedly across universities, study fields, and cohorts.

A.2 Construction of the SES-Index and the Reasons-Indices

Before applying the causal forest algorithm to analyze the heterogeneous treatment effects of the information intervention, I use principal component analysis to construct an index for measuring the socioeconomic status of students. I include monthly income in €, monthly parents' income in € in log-terms, confidence in parents' income, an indicator that is equal to 1 if parents are separated, an indicator for being a half-orphan, an indicator for believing that parents are relatively poor, migration background[19], potential civil servant status of

[16] The 18 fields are: Agricultural Sciences, Construction and Architecture, Biology and Chemistry, Electrical Engineering, Geosciences and Physics, Health Sciences, Medicine, Art, Mathematics and Computer Science, Mechanical Engineering, Pedagogy, Psychology, Law, Social Sciences, Linguistics and Cultural Sciences, Industrial Engineering, Economic Sciences, No clear allocation possible.

[17] Students in the first and second semester.

[18] Students in the third and fourth semester.

[19] Migration background is 0 if both the student and their parents were born in Germany, 1 if one out the three was born outside of Germany, 2 if two of them were born outside of Germany, and 3 if all were born

parents and parents' educational background[20]. The PCA yields that there is one principal component, which is used to construct the index. Using a cutoff of ± 0.3 for the factor loadings (Hair, 1998), the SES-Index comprises parents' income with the highest weight, followed by the belief that parents are relatively poor compared to other families, migration background, parents' education, and the half-orphan indicator. A higher SES-Index corresponds to a higher SES.

Analogously, I use PCA as a dimension reduction technique to comprise different reasons for non-take-up of student aid that students indicated on 5-point Likert scales. The PCA yields three components, where the first captures reasons related to the application or the student aid program. This index comprises the reasons "I do not want to be seen as a BAföG receiver", "I cannot provide the necessary certificate of performance", "I do not want to take on any debt", "The application is too time-consuming/complex", "My family situation is too complex for a BAföG application", "I do not wish to disclose any income information", and "I do not want to receive money from the state". The second index captures reasons that are related to their parents' income being too high for eligibility. The reasons are: "My parents have said that their income is too high", "I have realized myself that my parents' income is too high", and "I get enough financial support from my parents". The third index captures reasons that are related to the student's own financial situation. The reasons are: "My spouse's income is too high", "I have too much income myself", "I cannot receive BAföG due to previous training(s)", and "I have too many assets". The weights of the reasons that construct the three components are similarly high. Higher values in these components correspond to a higher agreement on the respective reasons why one has not applied for student aid so far. The two reasons "My application in the past was denied" and "The expected funding amount is positive but so low that it is not worth the effort" did not load on any of the three components and are therefore included separately in the analysis. The SES-Index and the three components of non-take-up reasons are used for the causal forest analysis instead of the variables they comprise.

A.3 Assumptions for Estimating the LATE

To estimate the local average treatment effect (LATE), five assumptions must be fulfilled (Angrist, Imbens & Rubin, 1996). These assumptions are discussed in the following. All assumptions are fulfilled.

outside of Germany.

[20] Parents' education is 0 if both parents do not have a university degree, 1 if one of them has a university degree, and 2 if both have a university degree.

1. **SUTVA**[21]: An individual's outcome is not affected by the treatment assigned to others. As explained in Section 4.2 and shown in Table C.13, I do not find any evidence for spillovers of the treatment, so the SUTVA holds.

2. **Independence**: Random assignment of the treatment.
   The information intervention was stratified, and the control and treatment group are balanced, shown in Table 1.

3. **Exclusion Restriction**: Treatment only affects take-up by correcting misperceptions.
   Given that the treatment is an information intervention that aims to correct misperceptions, it is unlikely that it increases take-up any other way than by correcting misperceptions about the student aid conditions and own eligibility.

4. **First Stage**: The intervention significantly corrects misperceptions.
   As shown in Tables 2 and 3, the intervention significantly corrects misperceptions both on student aid conditions and individual eligibility.

5. **Monotonicity**: The intervention only corrects misperceptions and does not worsen them.
   This is true by design for eligibility misperceptions, as I only look at misperceivers in the first place. For misperceptions about student aid conditions, we see a positive effect on corrections for underestimators and no effect for overestimators. Yet, since the effect is positive or zero but not negative, monotonicity is fulfilled.

A.4 Cost-Benefit Analysis

For the cost-benefit analysis, I first calculated the number of additional students who would receive student aid due to the intervention based on the 1.1 pp increase in take-up resulting from the intervention. In total, we have the following student numbers for 2023.

- In total, there are 2,868,311 enrolled students (Statistisches Bundesamt (Destatis), 2025c).
- Among them, 469,485 are foreigners and not eligible for student aid (Statistisches Bundesamt (Destatis), 2025c).
- Additionally, 359,847 already receive student aid (Statistisches Bundesamt (Destatis), 2025a).
- This leaves 2,038,979 students who could potentially receive aid.
- With an effect of 1.1pp, 22,429 students would receive student aid due to the intervention.

[21] Stable unit treatment value assumption.

If these students receive the average student aid of €663 per month (Statistisches Bundesamt (Destatis), 2025a), the overall increase in student aid is €178,445,124 per year. For the complete cost-benefit analysis, I assume that the students receive student aid from the beginning of their studies. A bachelor's student, therefore, receives in total €23,868 over 3 years, and a master's student receives in total €39,780 over 5 years. That is, both only repay the cap of €10,010. With a transition rate of 45% who start a master's program after completing their bachelor (Destatis, 2023b), the total student aid received is €695,935,984, and the repayment is €224,514,290, which amounts to the cost of the government for the additional student aid of €471,421,694.

Regarding the benefits of receiving student aid, assumptions are necessary. In the literature, receiving student aid has been shown to improve study pace, graduation rates, and post-college income. With respect to study pace, the literature has shown that receiving financial student aid increases the share of students who graduate earlier by 10% (Denning, Marx & Turner, 2019). For this context, I assume that when receiving student aid, students graduate 10% faster, so they graduate 4 months earlier in a bachelor's program, and 6 months earlier overall when also pursuing a master's degree. A bachelor's degree holder has an annual gross entry-level salary of €49,860 and a master's degree holder of €58,322. Since no official statistics of entry-level salaries for different educational degrees exist in Germany, I use these salaries from public administration jobs. Using a gross-net-calculator and assuming that the person is 27, is unmarried (tax class I), has no children, and lives in North Rhine-Westphalia, the most populous federal state in Germany, these income levels lead to an annual tax burden of €7,077 and €9,311, respectively. Assuming that everyone who receives student aid due to the 1.1 pp increase in take-up graduates eventually and taking the transition rate of 45% as given, the tax revenue of graduating earlier leads to a benefit of €76,129,073.

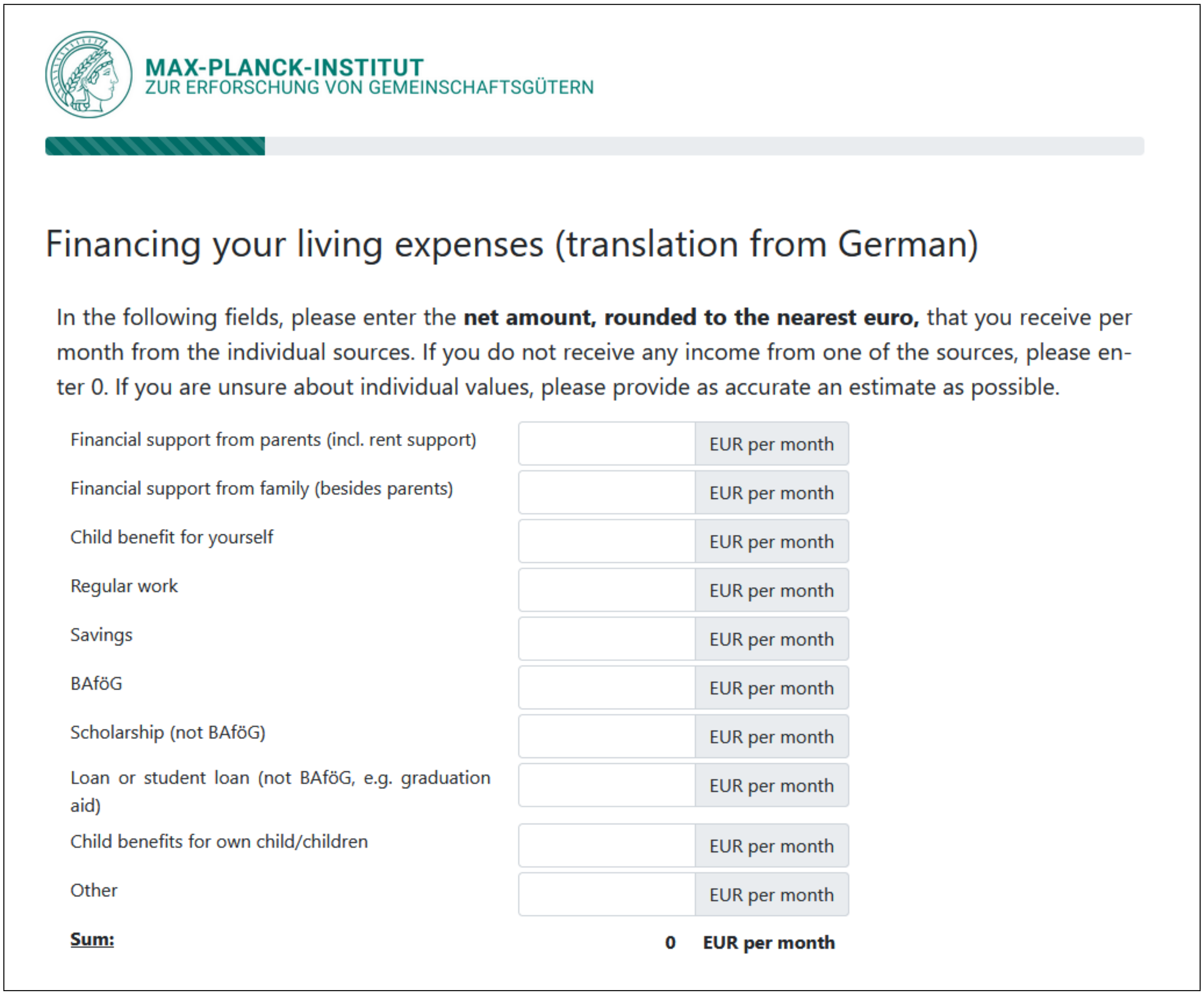
With respect to graduation rates, I assume that receiving student aid increases the likelihood of graduation by 8% (Bettinger et al., 2019; Denning, Marx & Turner, 2019; Fack & Grenet, 2015). For implementing this into the cost-benefit analysis, I take the transition rate of 45% as given for student aid recipients. That is, in the alternative without student aid, I assume that 8% less, so 41.7% graduate with a master's degree. These 8% of students still graduate with a bachelor's, but the 55% who never started a master's is reduced by 8%, leaving in total 54.3% who graduate with a bachelor's. The remaining 4.0% of students who drop out of the bachelor's program are assumed to complete vocational training.

With respect to income, the literature has found that student aid recipients earn 5-8% more per year later in life (Bettinger et al., 2019; Denning, Marx & Turner, 2019). For calculating the tax revenue that the student aid recipients generate, I use the average income per degree in Germany from 2024 (Statistisches Bundesamt (Destatis), 2025b). On average, students with vocational training have an annual gross income of €52,712, bachelor's degree holders of €68,729, and master's degree holders of €92,413. These income levels result in yearly tax burdens of €7,814, €12,567, and €21,776, respectively. With an additional 5%, a bachelor's degree holder earns on average €72,165 with a tax burden of €13,755, and a master's degree holder earns on average €97,034 with a tax burden of €23,948 per year. As before, I assume that everyone who receives student aid due to the 1.1 pp increase in take-up graduates eventually, and I take the transition rate of 45% as given. Assuming that every student works for 35 years, the student aid recipients generate an income tax revenue of €14,398,627,378 over their working life. In the alternative case without the income premium and with the adjusted transition rates, they generate an income tax revenue of €12,725,440,592. That is, the increase in graduation rates and income through student aid yields a benefit of €1,673,186,786.

Taken together, the overall cost of increasing student aid take-up by 1.1 pp is €471,421,694, while the overall benefit is €1,749,315,858. This leads to a net return of €1,277,894,164. That is, the investment in the students yields a return of 271% over the course of their working lives. However, this number has to be treated with caution, given the assumptions made. Yet, the size of the return shows that even with smaller effects, the return remains positive.

To this end, I have calculated the effect on the transition rate necessary for the state to break even, assuming no influence of student aid on study pace and post-college income. While the cost remains the same, an effect on the transition from bachelor's to master's programs of 6.6 pp (14.7%) is sufficient to break even. To calculate the benefit, I assume that the income of a bachelor's degree holder is on average €68,729 and of a master's degree holder is €92,413 with their respective tax burdens, as before. Increasing the transition rate of student aid recipients from 45% to 51.6% who enroll and graduate from a master's program after completing their bachelor's degree leads to an additional income tax revenue of €477,127,407 over the course of the students' working lives. The net return of the state is positive at €5,705,713,31. If student aid recipients also graduate 10% faster, as calculated above, an increase in the transition rate of 5.5 pp (12.2%), from 45% to 50.5%, is sufficient to break even with a net return of €2,313,551. This shows again that minor effects on the students' education are sufficient to yield positive income tax returns for the state on their investment of increasing student aid take-up by 1.1 pp.

Appendix B: Survey Screenshots



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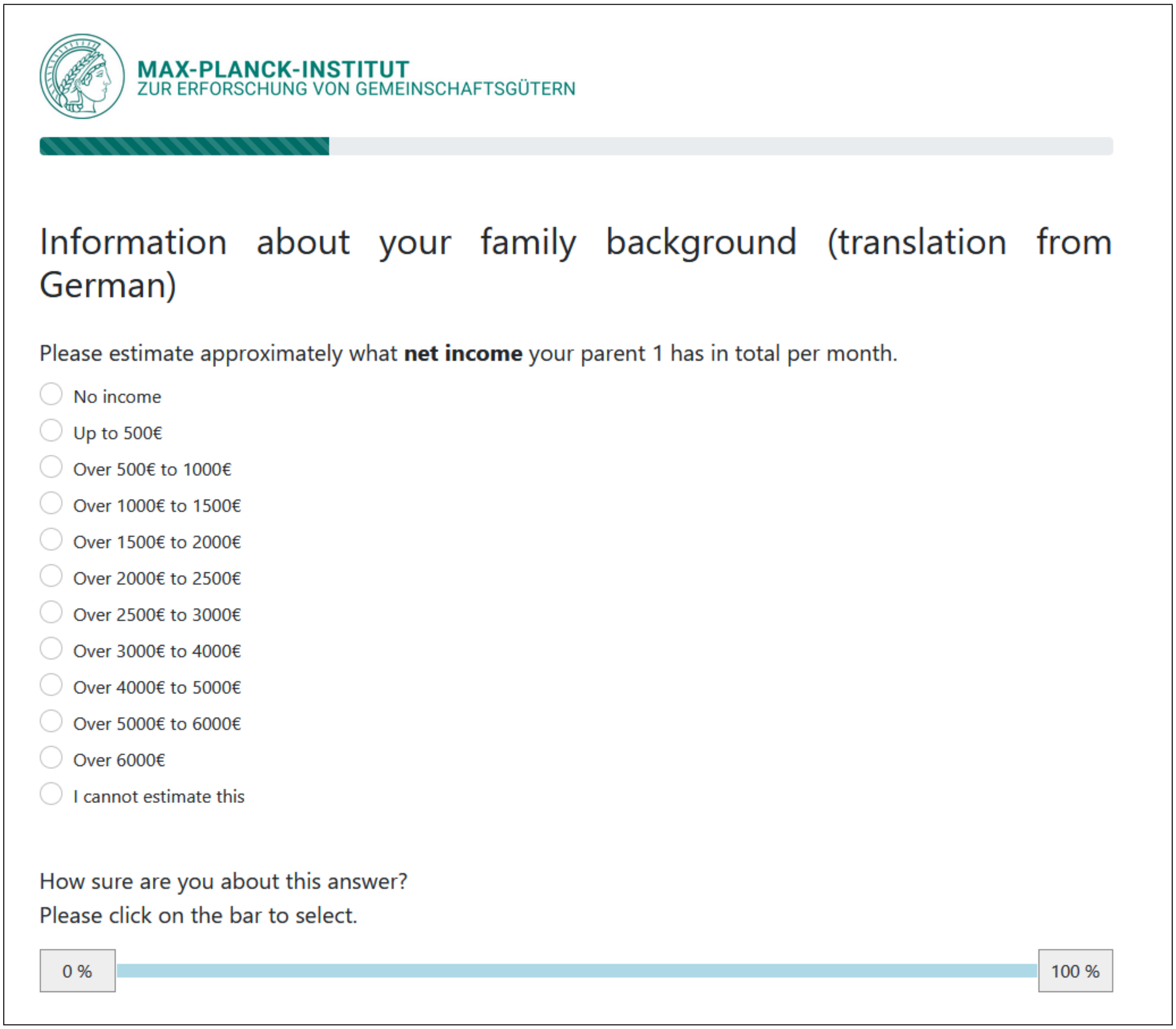
Financing your living expenses (translation from German)

In the following fields, please enter the **net amount, rounded to the nearest euro,** that you receive per month from the individual sources. If you do not receive any income from one of the sources, please enter 0. If you are unsure about individual values, please provide as accurate an estimate as possible.

Financial support from parents (incl. rent support)		EUR per month
Financial support from family (besides parents)		EUR per month
Child benefit for yourself		EUR per month
Regular work		EUR per month
Savings		EUR per month
BAföG		EUR per month
Scholarship (not BAföG)		EUR per month
Loan or student loan (not BAföG, e.g. graduation aid)		EUR per month
Child benefits for own child/children		EUR per month
Other		EUR per month
Sum:	**0**	**EUR per month**

Figure B.1: Question on student's income per month.



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Information about your family background (translation from German)

Please estimate approximately what **net income** your parent 1 has in total per month.

- No income
- Up to 500€
- Over 500€ to 1000€
- Over 1000€ to 1500€
- Over 1500€ to 2000€
- Over 2000€ to 2500€
- Over 2500€ to 3000€
- Over 3000€ to 4000€
- Over 4000€ to 5000€
- Over 5000€ to 6000€
- Over 6000€
- I cannot estimate this

How sure are you about this answer?
Please click on the bar to select.

0 % | 100 %

Figure B.2: Question on parents' income and confidence.

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Reasons against BAföG-application (translated from German)

Please enter the reasons why you so far did not apply for BAföG this semester/study year.
Tick the extent to which the reasons apply to you or not. You can select several reasons that apply to you.
If you are taking part in the survey from your smartphone, please use the landscape format for this question.

	Applies	**Rather applies**	**Rather does not apply**	**Does not apply**	**Cannot make a clear statement**
I get enough financial support from my parents					
My spouse's income is too high					
I cannot provide the necessary certificate of performance					
The expected funding amount is positive but so low that it is not worth it					
My family situation is too complex for a BAföG application					
I do not want to receive money from the state					
I have too many assets (e.g. car/savings account)					
I have realized myself that my parents' income is too high					
My application in the past was declined					
I cannot receive BAföG due to previous training(s)					
My parents have said that their income is too high					
I have too much income myself (through work and/or scholarship)					
Application process is too time-consuming / application is too complex					
I do not want to take on any debt					
I do not want to be seen as a BAföG receiver					
I do not wish to disclose any income information about myself and/or my parents to the BAföG office					
Other:					

Figure B.3: Question on reasons against applying for student aid.

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Information about BAföG (translated from German)

Have you ever looked into BAföG?
A married couple with 2 children can earn up to €120,000 gross per year and the children can still receive BAföG!

Here is some information about BAföG:

- **Parents' income thresholds:**
  Parents or single parents with two children may earn up to approx. €120,000 gross per year for the children's BAföG entitlement. For one child, the income threshold is around €85,000 gross per year. Your own BAföG entitlement increases with each sibling in training.
- **BAföG amount:**
  Last winter semester, the maximum BAföG rate was raised to €934 per month. With parental health insurance, the maximum rate is €812 per month.
- **Repayment:**
  Only half of the BAföG must be repaid, but never more than €10,010. The repayment can be spread over several years to avoid financial hardship or can be repaid in one lump sum with a discount of up to 21%.
- **Assets and own income:**
  Assets up to €15,000 (e.g. account balance) are not taken into account. Anything above this amount reduces the BAföG entitlement, but does not invalidate it.
  The same applies to your own income. A €520 job is exactly at the limit and is not taken into account. Any net income in excess of this is deducted from the BAföG entitlement.
- **Age:**
  Any student who is not older than 45 at the start of their studies can apply for BAföG.

Even if the application process can be time-consuming, it's worth it!
Click here for the official homepage and here for the BAföG-application.
Most student representative bodies at universities offer free BAföG counseling. If you would like more information or are interested in an informal exchange, you can also contact us via e-mail at an bafoeg@coll.mpg.de.

Figure B.4: Screenshot of the information intervention - Screen 1.

MAX-PLANCK-INSTITUT
ZUR ERFORSCHUNG VON GEMEINSCHAFTSGÜTERN

Information about BAföG (translated from German)

ATTENTION:
With the information you have provided in this study, you could receive between **X€** and **Y€** BAföG per month!
[In case the student fulfills requirements]
You could also be eligible for parent-independent BAföG due to your age and/or completed initial training.

[In case of non-positive student aid estimation] Unfortunately, we were unable to determine an individual BAföG estimate based on your information.
However, your parents can have a combined income of X€ to Y€ **net** per month without you losing your possible BAföG entitlement.
[In case the student fulfills requirements]
You could also be eligible for parent-independent BAföG due to your age and/or completed initial training.

This information is without guarantee!
The actual amount of BAföG depends on the individual case and is based on the actual income and family situation.

In order to secure a possible BAföG entitlement for May, you must submit an informal application to your BAföG office this month, as no BAföG is paid retroactively for the period before the first application.

If you would like more information or are interested in an informal exchange, you can also contact us via e-mail at bafoeg@coll.mpg.de.

Figure B.5: Screenshot of the information intervention - Screen 2.

Appendix C: Additional Results

Table C.1: Correct Values of Misperception Elicitation Scenarios

Scenario	Correct Value in €
Amounts of Student Aid	
Basis	762
Mother's income €20,000	341
Assets of €18,000	512
Income Thresholds for Parents	
Basis	50,000
Studying sister	74,000
Repayment Amounts	
Basis	4,500
Total aid of €30,000	10,010
Repayment in one sum	3,960

Notes: The table shows the correct values of each question asked for the misperception elicitation using hypothetical scenarios.

Table C.2: Summary Statistics - Participants after Initial Survey

	Non-Appliers (N=12296)		Appliers (N=9573)		Diff. t-test
Variable	Mean	SD	Mean	SD	p-value
Age	24.300	3.940	24.949	4.322	0.000
Female (=1)	0.628	0.483	0.657	0.475	0.000
Monthly Income in €	1047.316	558.276	1119.176	508.326	0.000
Monthly Student Aid in €	0.000	0.000	497.283	359.016	0.000
Single (=1)	0.962	0.191	0.961	0.194	0.611
Study year	3.601	1.912	3.528	1.912	0.005
Lives with parents (=1)	0.161	0.367	0.113	0.316	0.000
East Germany (=1)	0.186	0.389	0.264	0.441	0.000
Consent for Recontact (=1)	0.787	0.410	0.832	0.374	0.000

Notes: The table shows the summary statistics of the students who did not apply for student aid and those who did until the initial data collection. The last column shows the p-value corresponding to two-sided t-tests of the means of each group, respectively.

Table C.3: Differences between Potential and Experimental Sample

Variable	Potential Sample (N=9216) Mean	SD	Experimental Sample (N=6225) Mean	SD	Diff. t-test p-value
Info-Intervention (=1)	0.474	0.499	0.476	0.499	0.820
Age	24.314	3.910	24.300	3.948	0.830
Female (=1)	0.622	0.485	0.623	0.485	0.889
Monthly Income in Wave 1 in €	1043.772	498.171	1046.862	496.079	0.706
Single (=1)	0.962	0.192	0.964	0.185	0.345
Study year	3.616	1.912	3.645	1.905	0.346
Lives with parents (=1)	0.164	0.370	0.161	0.368	0.732
East Germany (=1)	0.182	0.386	0.180	0.384	0.753
Believes to be eligible (=1)	0.099	0.299	0.089	0.284	0.024
Misperception Area (in €)					
Amounts of Student Aid	-261.176	226.052	-264.599	220.249	0.349
Income Thresholds for Parents	-16581.55	24274.65	-15413.89	23920.48	0.003
Repayment Amounts	2843.178	4406.360	2827.063	4237.863	0.820

Notes: The table shows the summary statistics of the potential sample of non-recipients who participated in the initial survey and those who participated again in the follow-up and, therefore, comprise the experimental sample. The remaining participants were not part of the experimental sample as they did not participate in the follow-up. Hence, no outcome variables were elicited from them. Only non-recipients could participate in the experiment since they did not apply for student aid before the survey. The last column shows the p-value corresponding to two-sided t-tests of the means of each group, respectively.

Table C.4: Representativeness of Experimental Sample

Variable	Experimental Sample (N=6,225) Mean	SD	Representative Data (N=163,272) Mean	SD	Mean Diff.
Age	24.300	3.948	24.594	3.845	-0.294
Female (=1)	0.623	0.485	0.500	0.500	0.123
Monthly Income in €	1046.862	494.083	1057.148	1206.954	-10.286
Migration Background (=1)	0.204	0.403	0.195	0.396	0.009
Single (=1)	0.964	0.185	0.900	0.299	0.064
Study year	3.645	1.905	3.309	1.961	0.336
Lives with parents (=1)	0.161	0.368	0.263	0.440	-0.102
East Germany (=1)	0.180	0.384	0.180	0.384	0.000

Notes: The table shows the summary statistics of the experimental sample and representative data for students in Germany in 2021 (Becker et al., 2024). The representative data were constructed the same way as the experimental sample: student aid recipients and students ineligible for student aid for administrative reasons were dropped. The last column shows the p-value corresponding to two-sided t-tests of the means of each group, respectively.

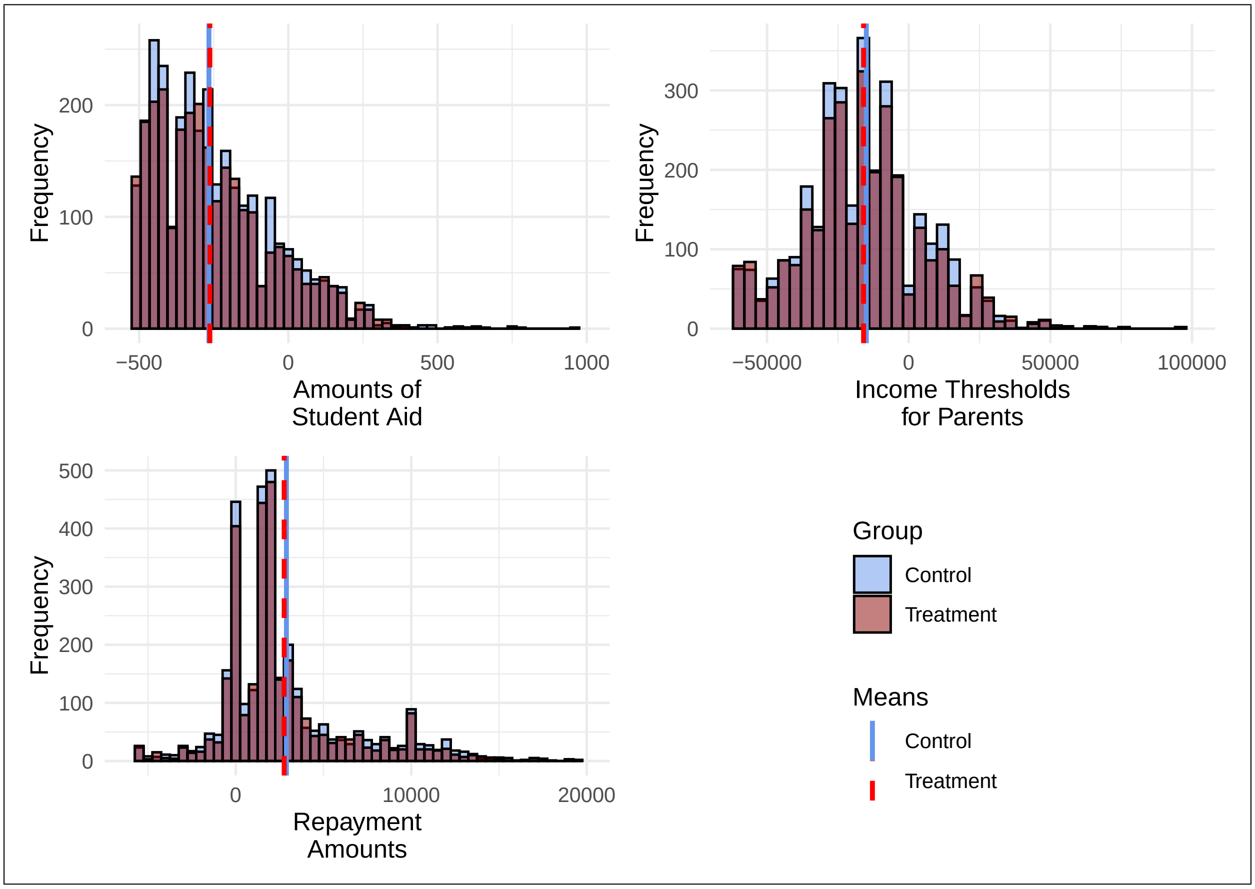

Figure C.1: Distribution of Average Misperceptions per Area.

Table C.5: Intervention Effect on Correcting Misperceptions

	Correction of Misperceptions (in pp)				
	Amounts of Student Aid	Income Thresh. for Parents	Repayment Amounts	Areas Pooled	Num. of Correct Answers
	(1)	(2)	(3)	(4)	(5)
Info-Intervention (=1)	0.037***	0.013	0.144***	0.058**	0.040***
	(0.008)	(0.009)	(0.042)	(0.024)	(0.010)
Intervention X Aid Realist/Optimist (=1)	−0.034**	−0.027*	−0.138***	−0.036	−0.019*
	(0.016)	(0.014)	(0.047)	(0.025)	(0.011)
Aid Realist/Optimist (=1)	0.046***	0.018*	0.260***	0.072***	0.046***
	(0.014)	(0.010)	(0.039)	(0.017)	(0.008)
Mean (Control Group Pessimists)	0.091	0.085	0.254	0.180	0.113
Observations	6,225	6,225	6,225	6,225	6,225
R^2	0.373	0.493	0.391	0.370	0.354
F Statistic	25.323***	41.360***	27.286***	24.966***	23.332***

Notes: The table shows the intervention effects on the correction of misperceptions from the initial to the follow-up survey. Misperceptions are measured as the absolute deviation from the correct values in the elicitation scenarios, divided by these correct values to determine the misperceptions in %. Misperceptions are averaged per area for columns (1)-(3), and over all areas for column (4). Column (5) uses the total number of misperceptions, measured as the number of answers to the elicitation scenarios outside the incentivized interval as explained in Section 3.2. The outcome is the correction in misperceptions, calculated as initial minus follow-up misperceptions, such that positive coefficients show a stronger correction of misperceptions in percentage points. *Aid Realists/Optimist* is equal to 1 if the participant overestimated or answered with the correct value of the misperception elicitation for at least one question per elicitation scenario. For the area "repayment amounts", the variable equals 1 if the participant underestimated or correctly answered at least one correct value, respectively. The positive coefficients in row 1 show that the intervention reduced misperceptions for the aid pessimists significantly.

I control for initial misperceptions, all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Table C.6: Intervention Effect on Correction of Misperceptions (Avg.)

	Correction of Misperceptions (in pp)				
	Amounts of Student Aid (1)	Income Thresh. for Parents (2)	Repayment Amounts (3)	Areas Pooled (4)	Num. of Correct Answers (5)
Info-Intervention (=1)	0.027***	0.012	0.053***	0.027***	0.029***
	(0.008)	(0.007)	(0.018)	(0.009)	(0.005)
Intervention X Aid Realist/Optimist (=1)	−0.023	−0.050***	−0.078	−0.003	−0.016**
	(0.025)	(0.016)	(0.058)	(0.016)	(0.008)
Aid Realist/Optimist (=1)	0.047**	0.025**	0.006	-0.002	0.015***
	(0.020)	(0.011)	(0.037)	(0.012)	(0.006)
Mean (Control Group Pessimists)	0.042	0.029	0.033	0.045	0.040
Observations	6,225	6,225	6,225	6,225	6,225
R^2	0.373	0.493	0.383	0.368	0.352
F Statistic	25.254***	41.425***	26.376***	24.718***	23.077***

Notes: The table shows the intervention effects on the correction of misperceptions from the initial to the follow-up survey. Misperceptions are measured as the absolute deviation from the correct values in the elicitation scenarios, divided by these correct values to determine the misperceptions in %. Misperceptions are averaged per area for columns (1)-(3), and over all areas for column (4). Column (5) uses the total number of misperceptions, measured as the number of answers to the elicitation scenarios outside the incentivized interval as explained in Section 3.2. The outcome is the correction in misperceptions, calculated as initial minus follow-up misperceptions, such that positive coefficients show a stronger correction of misperceptions in percentage points. *Aid Realist/Optimist* is equal to 1 if the participant on average overestimated or answered with the correct value of the respective misperception elicitation scenario. For the area "repayment amounts", the variable is equal to 1 if the participant underestimated the average correct value, respectively. The positive coefficients in row 1 show that the intervention reduced misperceptions for aid pessimists significantly.
I control for initial misperceptions, all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.7: Intervention Effect on Misperceptions About Own Eligibility (Intensive)

	Correction of Eligibility Misperceptions (Intensive, in pp)			
	Eligible students: excluding own income		Eligible students: including own income	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.035***	0.031**	0.046***	0.047***
	(0.012)	(0.012)	(0.014)	(0.014)
Mean Control Group	0.058	0.058	0.062	0.062
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	2,361	2,361	1,786	1,786
R^2	0.004	0.092	0.007	0.101
F Statistic	9.472***	1.746***	12.324***	1.483***

Notes: The table shows the intervention effects on the correction of misperceptions about the participants' own eligibility for student aid from the initial to the follow-up survey. Only participants are considered who are classified as eligible for student aid and initially misperceive this eligibility, so participants that do not believe to be eligible, hence answer the Likert scale question on perceived eligibility with "Rather No", "Definitely No", or "Cannot give a clear answer". The difference between answers to the perceived eligibility question from the initial to the follow-up survey is used as the outcome, divided by 4 to represent percentage terms. Every student who applied is assumed to definitely think they are eligible. That is, a student who answered "Definitely No" in the initial survey and "Definitely Yes" in the follow-up survey or applied for student aid has a correction of 1. To determine eligibility, the student's sociodemographic and economic situation excluding their own income is used for columns (1) and (2), and including their income for columns (3) and (4).

I control for all misperceptions from the scenarios, confidence in these answers, sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Table C.8: Intervention Effect on Student Aid Take-Up

	Take-Up of Student Aid (=1)		
	(1)	(2)	(3)
Info-Intervention (=1)	0.011***	0.010***	0.010***
	(0.004)	(0.004)	(0.004)
Mean Control Group	0.024	0.024	0.024
Controls	No	Yes	Yes
Study Field FE	No	No	Yes
University FE	No	No	Yes
Observations	6,225	6,225	6,225
R^2	0.001	0.068	0.079
F Statistic	6.580**	7.568***	3.855***

Notes: The table shows the intervention effect on take-up rates. Every student who indicated to receive student aid in the follow-ups or with a successful application is considered for take-up. Additionally, students classified as eligible based on their sociodemographic and economic situation, excluding their own income, who applied for student aid but did not have the final decision in the first follow-up and did not participate in the second follow-up were considered for take-up. The positive coefficients in row 1 show that the intervention led to significantly higher application rates by 1.0-1.1 pp.
I control for initial misperceptions per area, all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Coefficients for these variables are presented in Table C.9. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.9: Intervention Effect on Student Aid Take-Up (extended)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.010***	0.010***	0.007**	0.008**
	(0.004)	(0.004)	(0.003)	(0.003)
Misp. Amounts of Student Aid in W1 (in %)	−0.007	−0.007	−0.003	−0.003
	(0.009)	(0.008)	(0.008)	(0.008)
Confidence Misp. Amounts of Student Aid	−0.002	−0.003	0.001	−0.0002
	(0.014)	(0.014)	(0.014)	(0.014)
Misp. Income Thresholds for Parents in W1 (in %)	0.008	0.008	0.006	0.006
	(0.006)	(0.007)	(0.006)	(0.006)
Confidence Misp. Income Thresholds for Parents	0.001	0.004	−0.007	−0.003
	(0.017)	(0.017)	(0.017)	(0.018)
Misp. Repayment Amounts in W1 (in %)	−0.0003	−0.001	0.0001	−0.0002
	(0.004)	(0.004)	(0.004)	(0.004)
Confindence Misp. Repayment Amounts	0.022**	0.021**	0.021**	0.019*
	(0.011)	(0.011)	(0.010)	(0.010)
Age	0.001	0.001	0.0002	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Female (=1)	0.0001	−0.002	0.001	−0.002
	(0.004)	(0.004)	(0.005)	(0.005)
Married (=1)	−0.008	−0.011	−0.0001	−0.003
	(0.016)	(0.015)	(0.015)	(0.015)
Lives with parents (=1)	−0.015	−0.017	−0.011	−0.014
	(0.011)	(0.010)	(0.011)	(0.010)
East Germany (=1)	−0.006	0.006	−0.006	−0.002
	(0.006)	(0.015)	(0.005)	(0.015)
Master (=1)	0.003	0.009	−0.0003	0.005
	(0.007)	(0.008)	(0.007)	(0.008)
Second training (=1)	0.005	0.003	0.005	0.003
	(0.007)	(0.007)	(0.006)	(0.006)
Log(Monthly Income in Wave 1 in €)	−0.021***	−0.022***	−0.017***	−0.019***
	(0.007)	(0.007)	(0.006)	(0.006)
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	6,225	6,225	6,225	6,225
R^2	0.068	0.079	0.061	0.073
F Statistic	7.568***	3.855***	6.814***	3.548***

Notes: Continued on next page.

Table C.9: Intervention Effect on Student Aid Take-Up (extended) (contd.)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Log(Parents' monthly net income in €)	0.0003	−0.001	0.001	0.0003
	(0.005)	(0.005)	(0.005)	(0.005)
Confidence parents' Income	−0.0003	−0.002	−0.001	−0.003
	(0.011)	(0.011)	(0.010)	(0.010)
Parents handle finances (=1)	0.015	0.017	0.002	0.005
	(0.015)	(0.015)	(0.011)	(0.012)
Parents separate (=1)	−0.0001	−0.0004	−0.001	−0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Half-orphan (=1)	0.008	0.007	0.013	0.013
	(0.013)	(0.013)	(0.013)	(0.013)
Knows receivers (=1)	−0.004	−0.003	−0.004	−0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Believes parents are poor (=1)	0.014	0.014	0.014	0.014
	(0.010)	(0.010)	(0.010)	(0.010)
Num. of siblings	0.001	0.0004	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Study year	−0.004**	−0.005**	−0.003	−0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Moves out from parents (=1)	0.041**	0.045**	0.042**	0.046**
	(0.019)	(0.019)	(0.019)	(0.019)
Moves in to parents (=1)	−0.035***	−0.034***	−0.031***	−0.031***
	(0.006)	(0.006)	(0.005)	(0.005)
GPA	−0.0004	−0.00000	−0.002	−0.001
	(0.003)	(0.004)	(0.003)	(0.004)
Born outside Germany (=1)	−0.021*	−0.020	−0.029**	−0.028**
	(0.013)	(0.013)	(0.013)	(0.013)
Both parents born outside Germany (=1)	0.022*	0.023*	0.016	0.018
	(0.012)	(0.012)	(0.012)	(0.012)
Some parent born outside Germany (=1)	−0.004	−0.004	−0.001	−0.002
	(0.008)	(0.008)	(0.008)	(0.008)
Both parents civil servants (=1)	−0.003	−0.003	−0.001	−0.0003
	(0.008)	(0.008)	(0.008)	(0.008)
Some parent civil servant (=1)	−0.002	−0.003	−0.003	−0.004
	(0.005)	(0.005)	(0.004)	(0.005)
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	6,225	6,225	6,225	6,225
R^2	0.068	0.079	0.061	0.073
F Statistic	7.568***	3.855***	6.814***	3.548***

Notes: Continued on next page.

Table C.9: Intervention Effect on Student Aid Take-Up (extended) (contd.)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Both parents college degree (=1)	−0.002	−0.001	−0.002	−0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Some parent college degree (=1)	−0.014**	−0.013**	−0.014**	−0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
No longer student (=1)	0.002	0.004	0.003	0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Believes to be eligible (=1)	0.100***	0.100***	0.090***	0.090***
	(0.013)	(0.013)	(0.013)	(0.012)
Reason: Stigma (=1)	−0.007	−0.006	−0.003	−0.002
	(0.012)	(0.013)	(0.012)	(0.012)
Reason: Parents said so (=1)	−0.012**	−0.011**	−0.011**	−0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
Reason: Found out myself (=1)	0.001	−0.0002	0.002	0.001
	(0.005)	(0.005)	(0.004)	(0.004)
Reason: Partners' income (=1)	−0.003	−0.004	−0.006	−0.007
	(0.012)	(0.012)	(0.010)	(0.010)
Reason: Not enough ECTS (=1)	−0.016**	−0.015**	−0.016**	−0.015**
	(0.007)	(0.007)	(0.007)	(0.007)
Reason: Debt aversion (=1)	−0.016***	−0.016***	−0.015***	−0.015***
	(0.005)	(0.005)	(0.005)	(0.005)
Reason: Own income (=1)	−0.007	−0.007	−0.008	−0.008
	(0.006)	(0.006)	(0.006)	(0.006)
Reason: Complexity (=1)	0.001	0.001	0.004	0.004
	(0.005)	(0.005)	(0.004)	(0.004)
Reason: Application denied (=1)	−0.002	−0.001	−0.005	−0.004
	(0.007)	(0.007)	(0.006)	(0.007)
Reason: Second training (=1)	−0.009	−0.008	−0.009	−0.009
	(0.008)	(0.008)	(0.008)	(0.008)
Reason: Amount too small (=1)	−0.0003	−0.0002	−0.001	−0.001
	(0.006)	(0.006)	(0.006)	(0.006)
Reason: Family situation (=1)	0.002	0.002	0.002	0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	6,225	6,225	6,225	6,225
R^2	0.068	0.079	0.061	0.073
F Statistic	7.568***	3.855***	6.814***	3.548***

Notes: Continued on next page.

Table C.9: Intervention Effect on Student Aid Take-Up (extended) (contd.)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Reason: Privacy issues (=1)	−0.004	−0.004	−0.006	−0.005
	(0.007)	(0.007)	(0.006)	(0.006)
Reason: Enough support parents (=1)	−0.010	−0.009	-0.012^{**}	-0.011^{*}
	(0.006)	(0.006)	(0.005)	(0.006)
Reason: No money from state (=1)	−0.009	−0.010	−0.009	−0.011
	(0.007)	(0.007)	(0.007)	(0.007)
Reason: Wealth (=1)	−0.001	−0.001	−0.002	−0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Reason: Other (=1)	0.010	0.010	0.008	0.008
	(0.010)	(0.010)	(0.010)	(0.010)
Patience	−0.0005	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Impulsiveness	0.001	0.001	0.0001	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Debt Aversion	−0.001	−0.001	−0.0003	−0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.196^{***}	0.181^{***}	0.162^{***}	0.148^{**}
	(0.058)	(0.061)	(0.054)	(0.058)
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	6,225	6,225	6,225	6,225
R^2	0.068	0.079	0.061	0.073
F Statistic	7.568^{***}	3.855^{***}	6.814^{***}	3.548^{***}

Notes: The table shows the intervention effect on take-up rates. Every student who indicated to receive student aid in the follow-ups or with a successful application is considered for take-up. For columns 1 and 2, also students are considered for take-up who are classified as eligible based on their sociodemographic and economic situation (excluding their own income) and who indicated to have applied for student aid but did not have the final decision in the first follow-up and did not participate in the second follow-up.
The table shows the regression coefficient of all misperception, sociodemographic, reasons for non-take-up, and preference variables not displayed in columns 2 and 3 of Table C.8. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.10: Intervention Effect on Take-Up of Student Aid - Eligible Students (excluding own income)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.023***	0.022***	0.017**	0.017**
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.035***	0.355***	0.032***	0.322***
	(0.005)	(0.137)	(0.005)	(0.117)
Controls	No	Yes	No	Yes
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	2,718	2,718	2,718	2,718
R^2	0.003	0.121	0.002	0.111
F Statistic	8.379***	2.774***	4.941**	2.519***

Notes: The table shows the intervention effect on take-up rates for students who are classified as eligible for student aid based on their sociodemographic and economic situation without considering their own income. Every student who indicated to receive student aid in the follow-ups or with a successful application is considered for take-up. For columns 1 and 2, all students who were classified as eligible (excluding their income) and indicated that they had applied for student aid but did not participate in the second follow-up were considered for take-up.

I control for all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Table C.11: Intervention Effect on Take-Up of Student Aid - Eligible Students (including own income)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.027***	0.025***	0.018**	0.018**
	(0.009)	(0.009)	(0.008)	(0.009)
Constant	0.040***	0.412**	0.036***	0.405***
	(0.006)	(0.163)	(0.006)	(0.137)
Controls	No	Yes	No	Yes
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	2,072	2,072	2,072	2,072
R^2	0.004	0.136	0.002	0.126
F Statistic	7.383***	2.494***	3.956**	2.274***

Notes: The table shows the intervention effect on take-up rates for students who are classified as eligible for student aid based on their sociodemographic and economic situation including income. Every student who indicated to receive student aid in the follow-ups or with a successful application is considered for take-up. For columns 1 and 2, all students who were classified as eligible and indicated that they had applied for student aid but did not participate in the second follow-up were considered for take-up.
I control for all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.12: Information and Awareness Intervention Effects on Student Aid Applications

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.011***	0.010***	0.007**	0.007**
	(0.004)	(0.004)	(0.004)	(0.003)
Awareness-Intervention (=1)	0.028	0.013	0.012	−0.001
	(0.021)	(0.020)	(0.017)	(0.017)
Info X Awareness	−0.005	0.001	0.016	0.021
	(0.028)	(0.027)	(0.026)	(0.025)
Constant	0.023***	0.176***	0.022***	0.145**
	(0.003)	(0.060)	(0.003)	(0.058)
Controls	No	Yes	No	Yes
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	6,225	6,225	6,225	6,225
R^2	0.002	0.080	0.001	0.074
F Statistic	4.006***	3.809***	2.668**	3.511***

Notes: The table shows the effect of both the information and the cross-randomized awareness intervention on student aid applications. The awareness intervention was distributed to 200 students from both the control and treatment groups of the information intervention. Students were informed in an email that they could receive a positive amount of student aid if they applied. For columns 1 and 2, all students who were classified as eligible (excluding their income) and indicated to have applied for student aid but did not participate in the second follow-up were considered for take-up.
I control for all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.13: Intervention Effect on University Level Specifications

Specification	Number of Universities	Number of Students	Weighted ATE on Uni Level	p-value
University level	37	5779	0.0146	0.6235
Universities with N < 50	14	317	0.0502	0.4546
Universities with N >= 50	23	5462	0.0125	0.4884
>10% Students in City	16	2398	0.0116	0.8832
<=10% Students in City	21	3064	0.0133	0.3986
Enrolled > 10,000	25	4919	0.0117	0.7517
Enrolled <= 10,000	12	543	0.0199	0.1776
Citysize > 100,000	29	5115	0.0124	0.5572
Citysize <= 100,000	8	347	0.0143	0.5870

Notes: The table shows the intervention effect at the university level. For each specification, the average treatment effect is calculated where each university is used as one observation with weights for the number of students per university. The p-values show if these ATEs are significantly different from the overall treatment effect of 1.1 pp in the increase of take-up through the intervention based on weighted two-sided t-tests. All t-tests are insignificant.

Table C.14: Reasons for Non-Take-Up

Reasons for Non-take-up	Fraction of Students
I do not want to be seen as a BAföG receiver	0.032
My parents have said that their income is too high	0.570
I have realized myself that my parents' income is too high	0.603
My spouse's income is too high	0.031
I cannot provide the necessary certificate of performance	0.104
I do not want to take on any debt	0.407
I have too much income myself	0.237
Application process is too time-consuming / application is too complex	0.425
My application in the past was denied	0.131
I cannot receive BAföG due to previous training(s)	0.101
The expected funding is positive but so low that it is not worth it	0.238
My family situation is too complex for a BAföG application	0.127
I do not want to disclose any income information to the BAföG office	0.101
I get enough financial support from my parents	0.644
I do not want to receive money from the state	0.073
I have too many assents	0.448
Other	0.059
Other: Age	0.004
Other: Debt / Repayment	0.001
Other: Second training	0.001
Other: Own wealth	0.002
Other: Parents' / partner's wealth	0.002
Other: Own income	0.002
Other: Parents' / siblings' / partner's income	0.004
Other: Lack of knowledge	0.003
Other: High (bureaucratic) effort	0.005
Other: Own / siblings' application denied	0.008
Other: No support / contact to parent(s)	0.009
Other: Denial or small amount expected	0.007
Other: Not enough credit points / too stressful	0.000
Other: No interest / enough support / others more in need	0.005
Other: Other parent-related issue	0.003
Other: Bad experiences	0.003
Other: Not identifiable	0.003
Other: Miscellaneous	0.008

Notes: The table shows the fraction of students who indicated the reason why they did not apply for student aid. Reasons were elicited on a 5-point Likert scale. All "Definitely yes" and "Rather yes" answers are represented in the fractions. Students who indicated that another reason applied to them could specify this reason in an open text field. These answers were classified by two independent research assistants and harmonized by a third research assistant into the categories reported in this table.

Table C.15: Reasons Why Recipients in the Intervention Group Reacted to the Intervention

Reasons that motivated me to apply (=1)	Fraction of Students
The information that I could possibly expect a positive BAföG	0.905
I became more specifically aware of BAföG through the first survey	0.571
The information about the BAföG amount per month	0.548
The information about the amount of parental income	0.524
The information about the amount of my own assets	0.476
The information about the repayment amount of BAföG	0.357
The information about the amount of my own income	0.286
Other	0.190

Notes: The table shows the fraction of students who indicated the reason why they applied due to the information intervention. The reasons are measured on a 5-point Likert scale. If a student indicated for a specific reason that it applies or rather applies to them, they are represented in the fraction of indicating the specific reason, respectively.

Table C.16: Heterogeneous Intervention Effects on Student Aid Take-Up

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	−0.001	0.003	0.003	−0.008*
	(0.003)	(0.004)	(0.003)	(0.004)
SES-Index	−0.007***			−0.002
	(0.002)			(0.003)
Intervention X	0.030***			0.024***
Low Quintiles SES (=1)	(0.008)			(0.009)
Monthly Income (in %)		−0.009**		−0.012***
		(0.004)		(0.004)
Intervention X		0.019***		0.014**
Low Quintiles Income (=1)		(0.007)		(0.007)
Reasons: Parents' Income (Index)			−0.011***	−0.010***
			(0.002)	(0.002)
Intervention X			0.017**	0.007
Low Quintiles Reasons: P. Income (=1)			(0.008)	(0.009)
Calculated Entitlement (in 100€)	0.006***	0.008***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Mean Take-Up - High Quintiles Control	0.015	0.020	0.011	0.007
Mean Take-Up - Low Quintiles Control	0.037	0.029	0.044	0.058
Observations	6,225	6,225	6,225	6,225
R^2	0.038	0.032	0.041	0.046
F Statistic	2.987***	2.474***	3.177***	3.432***

Notes: The table shows results from OLS estimation of the heterogeneity driving variables and interaction terms on a dummy variable equal to 1 if the participant took up student aid since the initial survey. All students who were classified as eligible and indicated to have applied for student aid but did not participate in the second follow-up were considered for take-up. Explanatory variables were selected through causal random forest estimation. The SES-Index gives the socioeconomic status of students constructed using PCA. The index for reasons for non-take-up is constructed using PCA, where the more students indicated that their parents' income was why they did not apply, the higher the index. The individual income is divided by the average income of the whole sample to show effects in %. Low Quintiles dummies are equal to 1 if the participant ranked below the 40%-quantile on the SES-, the Reasons-Index, or income, respectively. I control for the calculated student aid entitlements. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.17: Heterogeneous Intervention Effects on Student Aid Take-Up (Conservative)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	-0.002	-0.001	0.002	-0.009^{**}
	(0.003)	(0.004)	(0.003)	(0.004)
SES-Index	-0.007^{***}			-0.002
	(0.002)			(0.003)
Intervention X	0.025^{***}			0.019^{**}
Low Quintiles SES (=1)	(0.008)			(0.009)
Monthly Income (in %)		-0.007^{*}		-0.009^{**}
		(0.004)		(0.004)
Intervention X		0.020^{***}		0.016^{**}
Low Quintiles Income (=1)		(0.007)		(0.007)
Reasons: Parents' Income (Index)			-0.011^{***}	-0.009^{***}
			(0.002)	(0.002)
Intervention X			0.013^{*}	0.005
Low Quintiles Reasons: P. Income (=1)			(0.007)	(0.008)
Calculated Entitlement (in 100€)	0.004^{***}	0.006^{***}	0.005^{***}	0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Mean Take-Up - High Quintiles Control	0.015	0.019	0.011	0.007
Mean Take-Up - Low Quintiles Control	0.034	0.028	0.041	0.052
Observations	6,225	6,225	6,225	6,225
R^2	0.033	0.028	0.036	0.040
F Statistic	2.557^{***}	2.170^{***}	2.782^{***}	3.003^{***}

Notes: The table shows results from OLS estimation of the heterogeneity driving variables and interaction terms on a dummy variable equal to 1 if the participant took up student aid since the initial survey. Explanatory variables were selected through causal random forest estimation. The SES-Index gives the socioeconomic status of students constructed using PCA. The index for reasons for non-take-up is constructed using PCA, where the more students indicated that their parents' income was why they did not apply, the higher the index. The individual income is divided by the average income of the whole sample to show effects in %. Low Quintiles dummies are equal to 1 if the participant ranked below the 40%-quantile on the SES-, the Reasons-Index, or income, respectively. I control for the calculated student aid entitlements. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.18: Heterogeneous Intervention Effects on Student Aid Take-Up - Eligible Students (excluding own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.007	0.008	0.006	−0.009
	(0.008)	(0.009)	(0.008)	(0.009)
SES-Index	−0.008**			−0.002
	(0.004)			(0.004)
Intervention X	0.034**			0.017
Low Quintiles SES (=1)	(0.017)			(0.018)
Monthly Income (in %)		−0.026***		−0.031***
		(0.009)		(0.009)
Intervention X		0.033**		0.026*
Low Quintiles Income (=1)		(0.015)		(0.015)
Reasons: Parents' Income (Index)			−0.013***	−0.011***
			(0.003)	(0.003)
Intervention X			0.035**	0.028
Low Quintiles Reasons: P. Income (=1)			(0.017)	(0.018)
Calculated Entitlement (in 100€)	0.006***	0.006***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Mean Take-Up - High Quintiles Control	0.023	0.029	0.023	0.013
Mean Take-Up - Low Quintiles Control	0.052	0.043	0.043	0.080
Observations	2,718	2,718	2,718	2,718
R^2	0.047	0.047	0.054	0.064
F Statistic	1.761***	1.780***	2.039***	2.297***

Notes: The table shows results from OLS estimation of the heterogeneity driving variables and interaction terms on a dummy variable equal to 1 if the participant took up student aid since the initial survey. The sample is restricted to students who were classified as eligible for student aid based on their sociodemographic and economic situation excluding their own income. All students who were classified as eligible and indicated to have applied for student aid but did not participate in the second follow-up were considered for take-up. Explanatory variables were selected through causal random forest estimation. The SES-Index gives the socioeconomic status of students constructed using PCA. The index for reasons for non-take-up is constructed using PCA, where the more students indicated that their parents' income was why they did not apply, the higher the index. The individual income is divided by the average income of the whole sample to show effects in %. Low Quintiles dummies are equal to 1 if the participant ranked below the 40th percentile on the SES-, the Reasons-Index, or income, respectively. I control for the calculated student aid entitlements. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.19: Heterogeneous Intervention Effects on Student Aid Take-Up (Conservative) - Eligible Students (excluding own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.007	0.001	0.004	−0.010
	(0.008)	(0.008)	(0.007)	(0.009)
SES-Index	-0.007^{**}			−0.003
	(0.004)			(0.004)
Intervention X	0.021			0.007
Low Quintiles SES (=1)	(0.015)			(0.017)
Monthly Income (in %)		-0.021^{**}		-0.025^{***}
		(0.008)		(0.009)
Intervention X		0.038^{***}		0.032^{**}
Low Quintiles Income (=1)		(0.013)		(0.013)
Reasons: Parents' Income (Index)			-0.012^{***}	-0.011^{***}
			(0.003)	(0.003)
Intervention X			0.025^{*}	0.022
Low Quintiles Reasons: P. Income (=1)			(0.014)	(0.016)
Calculated Entitlement (in 100€)	0.005^{***}	0.005^{***}	0.005^{***}	0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Mean Take-Up - High Quintiles Control	0.023	0.027	0.019	0.013
Mean Take-Up - Low Quintiles Control	0.045	0.040	0.053	0.080
Observations	2,718	2,718	2,718	2,718
R^2	0.040	0.043	0.047	0.056
F Statistic	1.497^{***}	1.618^{***}	1.762^{***}	2.018^{***}

Notes: The table shows results from OLS estimation of the heterogeneity driving variables and interaction terms on a dummy variable equal to 1 if the participant took up student aid since the initial survey. The sample is restricted to students who were classified as eligible for student aid based on their sociodemographic and economic situation excluding their own income. Explanatory variables were selected through causal random forest estimation. The SES-Index gives the socioeconomic status of students constructed using PCA. The index for reasons for non-take-up is constructed using PCA, where the more students indicated that their parents' income was why they did not apply, the higher the index. The individual income is divided by the average income of the whole sample to show effects in %. Low Quintiles dummies are equal to 1 if the participant ranked below the 40th percentile on the SES-, the Reasons-Index, or income, respectively. I control for the calculated student aid entitlements. Study field and university fixed effects are included. Clustered standard errors are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Table C.20: Heterogeneous Intervention Effects on Student Aid Take-Up - Eligible Students (including own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.010	0.008	0.009	−0.007
	(0.009)	(0.011)	(0.010)	(0.010)
SES-Index	-0.009^{**}			−0.002
	(0.005)			(0.005)
Intervention X Low Quintiles SES (=1)	0.035			0.020
	(0.022)			(0.024)
Monthly Income (in %)		-0.041^{***}		-0.040^{***}
		(0.011)		(0.011)
Intervention X Low Quintiles Income (=1)		0.040^{**}		0.033^{*}
		(0.018)		(0.018)
Reasons: Parents' Income (Index)			-0.017^{***}	-0.014^{***}
			(0.004)	(0.004)
Intervention X Low Quintiles Reasons: P. Income (=1)			0.031	0.021
			(0.021)	(0.023)
Calculated Entitlement (in 100€)	0.005^{***}	0.007^{***}	0.005^{***}	0.003^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
Mean Take-Up - High Quintiles Control	0.026	0.033	0.024	0.013
Mean Take-Up - Low Quintiles Control	0.060	0.049	0.065	0.088
Observations	2,072	2,072	2,072	2,072
R^2	0.048	0.054	0.056	0.069
F Statistic	1.500^{***}	1.674^{***}	1.761^{***}	2.066^{***}

Notes: The table shows results from OLS estimation of the heterogeneity driving variables and interaction terms on a dummy variable equal to 1 if the participant took up student aid since the initial survey. The sample is restricted to students who were classified as eligible for student aid based on their sociodemographic and economic situation, including their income. All students who were classified as eligible and indicated to have applied for student aid but did not participate in the second follow-up were considered for take-up. Explanatory variables were selected through causal random forest estimation. The SES-Index gives the socioeconomic status of students constructed using PCA. The index for reasons for non-take-up is constructed using PCA, where the more students indicated that their parents' income was why they did not apply, the higher the index. The individual income is divided by the average income of the whole sample to show effects in %. Low Quintiles dummies are equal to 1 if the participant ranked below the 40th percentile on the SES-, the Reasons-Index, or income, respectively. I control for the calculated student aid entitlements. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table C.21: Heterogeneous Intervention Effects on Student Aid Take-Up (Conservative) - Eligible Students (including own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.007	−0.004	0.007	−0.012
	(0.009)	(0.010)	(0.009)	(0.009)
SES-Index	−0.009*			−0.002
	(0.004)			(0.005)
Intervention X	0.022			0.010
Low Quintiles SES (=1)	(0.020)			(0.022)
Monthly Income (in %)		−0.031***		−0.030***
		(0.010)		(0.010)
Intervention X		0.051***		0.046***
Low Quintiles Income (=1)		(0.016)		(0.016)
Reasons: Parents' Income (Index)			−0.016***	−0.013***
			(0.004)	(0.004)
Intervention X			0.019	0.012
Low Quintiles Reasons: P. Income (=1)			(0.017)	(0.019)
Calculated Entitlement (in 100€)	0.004**	0.005***	0.004**	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Mean Take-Up - High Quintiles Control	0.026	0.030	0.019	0.013
Mean Take-Up - Low Quintiles Control	0.051	0.045	0.063	0.088
Observations	2,072	2,072	2,072	2,072
R^2	0.041	0.050	0.049	0.063
F Statistic	1.267*	1.565***	1.507***	1.851***

Notes: The table shows results from OLS estimation of the heterogeneity driving variables and interaction terms on a dummy variable equal to 1 if the participant took up student aid since the initial survey. The sample is restricted to students who were classified as eligible for student aid based on their sociodemographic and economic situation, including their income. Explanatory variables were selected through causal random forest estimation. The SES-Index gives the socioeconomic status of students constructed using PCA. The index for reasons for non-take-up is constructed using PCA, where the more students indicated that their parents' income was why they did not apply, the higher the index. The individual income is divided by the average income of the whole sample to show effects in %. Low Quintiles dummies are equal to 1 if the participant ranked below the 40th percentile on the SES-, the Reasons-Index, or income, respectively. I control for the calculated student aid entitlements. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table C.22: Relative Changes in Income of Eligible Students over Time

	Relative Income (in %)					
	Total		from Work		from Parents	
	(1)	(2)	(3)	(4)	(5)	(6)
Take-Up (=1)	-0.162^{***}	-0.151^{***}	-0.239^{**}	-0.201^{*}	-0.148^{**}	-0.177^{***}
	(0.050)	(0.052)	(0.110)	(0.121)	(0.061)	(0.063)
Follow-up 1 (=1)	0.043^{***}	0.061^{***}	0.148^{***}	0.269^{***}	-0.039^{***}	-0.049^{***}
	(0.008)	(0.010)	(0.020)	(0.029)	(0.011)	(0.012)
Follow-up 2 (=1)	0.127^{***}	0.161^{***}	0.350^{***}	0.551^{***}	-0.022	-0.033^{**}
	(0.011)	(0.012)	(0.027)	(0.038)	(0.014)	(0.014)
Take-Up (=1) X	0.080^{*}	0.101^{**}	-0.139^{*}	-0.206^{**}	-0.081^{*}	-0.093^{*}
Follow-up 1 (=1)	(0.046)	(0.051)	(0.083)	(0.094)	(0.049)	(0.052)
Take-Up (=1) X	0.121^{**}	0.195^{***}	-0.446^{***}	-0.449^{***}	-0.158^{***}	-0.171^{***}
Follow-up 2 (=1)	(0.053)	(0.054)	(0.124)	(0.122)	(0.052)	(0.055)
Reference Income in €	1024.79	936.28	379.87	280.43	497.67	524.58
Eligible Students	excl. inc	incl. inc	excl. inc	incl. inc	excl. inc	incl. inc
Observations	4,665	3,639	4,755	3,708	4,755	3,708
R^2	0.111	0.140	0.113	0.140	0.164	0.194
F Statistic	578.324^{***}	588.960^{***}	600.770^{***}	597.847^{***}	927.483^{***}	886.349^{***}

Notes: The table shows results from an OLS panel regression with individual-level random effects of relative income over time for students who are classified as eligible for student aid in the initial survey. For each regression, I determine eligibility excluding students' income in the first column and including it in the second column, respectively. Relative Income is measured as the absolute income participants report in each survey, divided by the average income in the initial survey of participants who do not take up student aid, to measure the relative change compared to this reference group. *Follow-up 1* and *Follow-up 2* are equal to 1 for the respective period, and *Take-Up* is 1 for all participants who take up student aid in the first or the second follow-up. I control for sociodemographic characteristics. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Appendix D: Probit Regressions on Take-Up

Table D.1: Intervention Effect on Student Aid Take-Up

	Take-Up of Student Aid (=1)					
		Inclusive			Conservative	
	(1)	(2)	(3)	(4)	(5)	(6)
Info-Intervention (=1)	0.166***	0.166**	0.198***	0.132**	0.125*	0.149**
	(0.056)	(0.065)	(0.072)	(0.058)	(0.067)	(0.075)
Constant	−1.985***	0.113	−7.587***	−2.007***	−0.111	−7.743***
	(0.044)	(0.873)	(0.989)	(0.046)	(0.913)	(1.021)
Controls	No	Yes	Yes	No	Yes	Yes
Study Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	6,225	6,225	6,225	6,225	6,225	6,225

Notes: The table shows the results of Table C.8 using Probit estimation instead of OLS.
I control for misperceptions per area in the first wave, all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.2: Intervention Effect on Take-Up of Student Aid - Eligible Students (without own income)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.243***	0.311***	0.194**	0.241**
	(0.076)	(0.110)	(0.082)	(0.117)
Constant	−1.812***	−7.527***	−1.850***	−7.429***
	(0.062)	(1.567)	(0.065)	(1.548)
Controls	No	Yes	No	Yes
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	2,718	2,718	2,718	2,718

Notes: The table shows the results of Table C.10 using Probit estimation instead of OLS.
I control for all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.3: Intervention Effect on Take-Up of Student Aid - Eligible Students (with own income)

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.250***	0.301**	0.193**	0.219
	(0.084)	(0.124)	(0.088)	(0.134)
Constant	−1.756***	−3.893**	−1.801***	−3.313*
	(0.068)	(1.793)	(0.071)	(1.778)
Controls	No	Yes	No	Yes
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	2,072	2,072	2,072	2,072

Notes: The table shows the results of Table C.11 using Probit estimation instead of OLS. I control for all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.4: Causal Effect of Correcting Misperceptions on Student Aid Take-Up (LATE)

	Take-Up of Student Aid (=1)					
	Eligible Students:					
	excl. own income		incl. own income		Scenarios	
	Binary	*Likert*	*Binary*	*Likert*	*Pooled*	*Total*
	(1)	(2)	(3)	(4)	(5)	(6)
Correction of Misperceptions (in %)	12.903** (5.039)	12.511** (4.886)	8.559*** (3.275)	9.554*** (3.655)	7.769*** (2.772)	8.577*** (3.060)
Observations	2,361	2,361	1,786	1,786	6,225	6,225
1st stage F Statistic	4.330	6.487	9.642	11.597	14.475	24.503

Notes: The table shows the results of Table 4 using Probit estimation for the second stage instead of OLS. I control for all misperceptions from the scenarios, confidence in these answers, sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects in both stages. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.5: Information and Awareness Intervention Effects on Student Aid Take-Up

	Take-Up of Student Aid (=1)			
	Inclusive		Conservative	
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.172***	0.205***	0.124**	0.136*
	(0.058)	(0.075)	(0.059)	(0.076)
Awareness-Intervention (=1)	0.363*	0.211	0.185	0.021
	(0.205)	(0.254)	(0.232)	(0.300)
Info X Awareness	−0.116	−0.106	0.121	0.222
	(0.265)	(0.322)	(0.285)	(0.354)
Constant	−2.003***	−7.658***	−2.015***	−7.803***
	(0.048)	(0.997)	(0.048)	(1.029)
Controls	No	Yes	No	Yes
Study Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes
Observations	6,225	6,225	6,225	6,225

Notes: The table shows the results of Table C.12 using Probit estimation for the second stage instead of OLS.
I control for all sociodemographic and other control variables mentioned in Section 3, as well as reasons for non-take-up and study field and university fixed effects. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.6: Heterogeneous Intervention Effects on Student Aid Take-Up

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	−0.118	0.049	0.042	−0.198
	(0.095)	(0.082)	(0.101)	(0.128)
SES-Index	−0.096***			−0.022
	(0.024)			(0.030)
Intervention X	0.463***			0.388***
Low Quintiles SES (=1)	(0.116)			(0.140)
Monthly Income (in %)		−0.197*		−0.227**
		(0.109)		(0.099)
Intervention X		0.230**		0.171
Low Quintiles Income (=1)		(0.101)		(0.113)
Reasons: Parents' Income (Index)			−0.191***	−0.178***
			(0.030)	(0.035)
Intervention X			0.183	0.035
Low Quintiles Reasons: P. Income (=1)			(0.122)	(0.142)
Calculated Entitlement (in 100€)	0.064***	0.086***	0.067***	0.050***
	(0.011)	(0.010)	(0.010)	(0.011)
Observations	6,225	6,225	6,225	6,225

Notes: The table shows the results of Table C.16 using Probit estimation for the second stage instead of OLS. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.7: Heterogeneous Intervention Effects on Student Aid Take-Up (Conservative)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	−0.127	−0.018	0.015	−0.243*
	(0.098)	(0.088)	(0.103)	(0.132)
SES-Index	−0.097***			−0.023
	(0.025)			(0.032)
Intervention X	0.426***			0.347**
Low Quintiles SES (=1)	(0.122)			(0.145)
Monthly Income (in %)		−0.157		−0.188*
		(0.107)		(0.097)
Intervention X		0.291***		0.243**
Low Quintiles Income (=1)		(0.105)		(0.115)
Reasons: Parents' Income (Index)			−0.190***	−0.178***
			(0.031)	(0.036)
Intervention X			0.172	0.037
Low Quintiles Reasons: P. Income (=1)			(0.125)	(0.143)
Calculated Entitlement (in 100€)	0.054***	0.074***	0.056***	0.039***
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	6,225	6,225	6,225	6,225

Notes: The table shows the results of Table C.17 using Probit estimation for the second stage instead of OLS. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.8: Heterogeneous Intervention Effects on Student Aid Take-Up - Eligible Students (excluding own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.074	0.149	0.083	−0.046
	(0.116)	(0.130)	(0.132)	(0.168)
SES-Index	−0.075**			−0.022
	(0.033)			(0.038)
Intervention X	0.296*			0.142
Low Quintiles SES (=1)	(0.158)			(0.178)
Monthly Income (in %)		−0.436**		−0.459***
		(0.188)		(0.171)
Intervention X		0.176		0.140
Low Quintiles Income (=1)		(0.153)		(0.163)
Reasons: Parents' Income (Index)			−0.169***	−0.163***
			(0.042)	(0.046)
Intervention X			0.232	0.182
Low Quintiles Reasons: P. Income (=1)			(0.167)	(0.187)
Calculated Entitlement (in 100€)	0.059***	0.060***	0.062***	0.039***
	(0.013)	(0.013)	(0.012)	(0.014)
Observations	2,718	2,718	2,718	2,718

Notes: The table shows the results of Table C.18 using Probit estimation for the second stage instead of OLS. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.9: Heterogeneous Intervention Effects on Student Aid Take-Up (Conservative) - Eligible Students (excluding own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.066	0.033	0.058	-0.127
	(0.123)	(0.142)	(0.141)	(0.183)
SES-Index	-0.079^{**}			-0.027
	(0.036)			(0.040)
Intervention X	0.230			0.079
Low Quintiles SES (=1)	(0.170)			(0.193)
Monthly Income (in %)		-0.355^{*}		-0.386^{**}
		(0.185)		(0.169)
Intervention X		0.309^{*}		0.287^{*}
Low Quintiles Income (=1)		(0.159)		(0.170)
Reasons: Parents' Income (Index)			-0.172^{***}	-0.166^{***}
			(0.046)	(0.050)
Intervention X			0.196	0.169
Low Quintiles Reasons: P. Income (=1)			(0.169)	(0.194)
Calculated Entitlement (in 100€)	0.052^{***}	0.051^{***}	0.054^{***}	0.030^{**}
	(0.014)	(0.014)	(0.013)	(0.015)
Observations	2,718	2,718	2,718	2,718

Notes: The table shows the results of Table C.19 using Probit estimation for the second stage instead of OLS. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.10: Heterogeneous Intervention Effects on Student Aid Take-Up - Eligible Students (including own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.111	0.123	0.149	−0.009
	(0.116)	(0.143)	(0.143)	(0.164)
SES-Index	-0.087^{**}			−0.021
	(0.038)			(0.044)
Intervention X	0.236			0.151
Low Quintiles SES (=1)	(0.180)			(0.203)
Monthly Income (in %)		-0.572^{***}		-0.519^{***}
		(0.169)		(0.155)
Intervention X		0.219		0.211
Low Quintiles Income (=1)		(0.164)		(0.171)
Reasons: Parents' Income (Index)			-0.207^{***}	-0.189^{***}
			(0.047)	(0.051)
Intervention X			0.121	0.058
Low Quintiles Reasons: P. Income (=1)			(0.179)	(0.200)
Calculated Entitlement (in 100€)	0.046^{***}	0.067^{***}	0.045^{***}	0.036^{**}
	(0.015)	(0.015)	(0.015)	(0.017)
Observations	2,072	2,072	2,072	2,072

Notes: The table shows the results of Table C.20 using Probit estimation for the second stage instead of OLS. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table D.11: Heterogeneous Intervention Effects on Student Aid Take-Up (Conservative) - Eligible Students (including own income)

	Take-Up of Student Aid (=1)			
	(1)	(2)	(3)	(4)
Info-Intervention (=1)	0.091	-0.051	0.124	-0.147
	(0.131)	(0.161)	(0.153)	(0.191)
SES-Index	-0.090^{**}			-0.024
	(0.042)			(0.048)
Intervention X	0.174			0.116
Low Quintiles SES (=1)	(0.189)			(0.209)
Monthly Income (in %)		-0.464^{***}		-0.414^{***}
		(0.173)		(0.158)
Intervention X		0.434^{**}		0.442^{**}
Low Quintiles Income (=1)		(0.175)		(0.181)
Reasons: Parents' Income (Index)			-0.210^{***}	-0.195^{***}
			(0.053)	(0.057)
Intervention X			0.073	0.013
Low Quintiles Reasons: P. Income (=1)			(0.179)	(0.196)
Calculated Entitlement (in 100€)	0.042^{**}	0.060^{***}	0.038^{**}	0.029
	(0.017)	(0.016)	(0.016)	(0.019)
Observations	2,072	2,072	2,072	2,072

Notes: The table shows the results of Table C.21 using Probit estimation for the second stage instead of OLS. Study field and university fixed effects are included. Clustered standard errors are in parentheses.
*p<0.1; **p<0.05; ***p<0.01