Confidence and College Applications: Evidence from a Randomized Intervention*

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Abstract

This paper examines how student confidence influences college applications. Using experiments with over 2,000 French students, we show that top female and low-SES students significantly underestimate their academic rank compared to male and high-SES peers. Matching survey data with administrative records, we show that this underconfidence impacts college choices. A randomized intervention correcting students' rank perceptions offset this effect and encouraged underconfident students to apply to more prestigious programs, especially females and low-SES students. In our sample, the intervention reduced the gender gap in elite college admissions by 72% and the social gap by 95% without increasing dropout rates.

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1 Introduction

Access to prestigious colleges and high-paying careers varies substantially by gender and social background. In the US, children with parents in the top 1% of the income distribution are 77 times more likely to attend elite colleges and universities than children with parents in the bottom 20% of the income distribution (Chetty et al., 2020, 2023; Hoxby and Avery, 2012). Gender also plays a key role. Controlling for grades, females disproportionately enter less selective colleges and lower-paying jobs than men (Saygin, 2016; Blau and Kahn, 2017). A variety of factors have been identified as contributing to unequal access to college, from financial constraints (Angrist et al., 2022; Bettinger et al., 2019; Dynarski, 2000; Scott-Clayton and Schudde, 2020) to preferences for programs or peers (Wiswall and Zafar, 2015, 2018; Patnaik et al., 2021), and information frictions (Bettinger et al., 2012; Hoxby and Turner, 2015; Bergman et al., 2019). There has also been growing interest in understanding behavioral barriers to college access, with research exploring the role played by complexity and uncertainty in the admissions and financial aid process (Dynarski et al., 2021) and competitiveness (Buser et al., 2014, 2020; Boneva et al., 2021; Reuben et al., 2019).

This paper considers a novel behavioral barrier to college access, namely students' over- and underconfidence regarding their academic ability. We refer to these phenomena as "misconfidence," which is defined as the difference between student *perception* of their rank in the grade distribution and their *real* rank in the distribution.[1] It is very common for individuals to have biased beliefs about their own abilities (Niederle and Vesterlund, 2007; Moore and Healy, 2008; Möbius et al., 2022; Burks et al., 2013). While several studies show a correlation between confidence and educational choices (Carlana et al., 2022; Falk et al., 2020; Guyon and Huillery, 2020), we lack causal evidence on the effect of misconfidence on college applications and admissions.

We combine survey and administrative data (on college applications, admissions, and dropout) with a randomized intervention to answer three questions: First, how large are confidence gaps by gender and socioeconomic status (SES)? Second, is misconfidence associated with college applications and admissions? Third, is the relationship causal, i.e., how effective is an intervention that provides students with feedback on their real rank in the grade distribution at mitigating the role played by misconfidence in college applications, and does this intervention help close gender and social gaps in college admission?

The question of how confidence affects college choice is paramount from both an efficiency and an equity perspective. From an efficiency perspective, over- and un-

[1] Incorrect beliefs about relative position in the distribution are often referred to as over- and underplacement (Moore and Healy, 2008).

derconfidence can be costly. Underconfident students might shy away from the most prestigious colleges, wrongly believing they have low admission chances. These students may realize, after the allocation is finalized, that they could have been admitted to colleges they liked more had they applied there. This distorts the stability of the final student-college match, meaning that students do not attend their most preferred college among those to which they could have been admitted.[2] Overconfidence is also costly as students might aim too high and end up unmatched (Arteaga et al., 2022).[3]

From an equity perspective, studying the link between confidence and college choice is essential because of the well-documented gender and social gaps in confidence (e.g., Niederle and Vesterlund, 2007; Almås et al., 2016; Guyon and Huillery, 2020; Bobba and Frisancho, 2022). Underconfidence among female and low-SES students can discourage them from applying to prestigious programs, an aspiration gap that has been extensively documented, and that we confirm in France (the context of this study).[4] Among top students who receive the best grades, female and low-SES students are respectively 20.0 and 14.7 points less likely to apply to an elite program (known as *classes préparatoires* or CPGE) than their male and high-SES peers. These large aspiration gaps are concerning as prestigious colleges usually have higher returns (Zimmerman, 2019; Anelli, 2020; Altonji et al., 2016; Kirkeboen et al., 2016; Hastings et al., 2013), and enrollment in selective colleges can especially benefit low-SES students (Black et al., 2023; Bleemer, 2024).

The French context is very suitable for studying the role of confidence in college choices for four reasons. First, 84% of students enroll in free public institutions.[5] The absence of financial constraints is critical for studying social aspiration gaps, as boosting confidence may not influence low-SES students' college choices if they face financial barriers. Second, students can apply to only a limited number of programs, forcing them to consider feasibility before applying. Third, there is no centralized college entrance exam in France, contributing to misperceptions about one's position in the ability distribution. This situation is common globally (e.g., Canada, Germany, Austria, Belgium, Mexico, the Netherlands, Denmark, Finland, Italy (except certain

[2]Stability is important in countries utilizing stable matching mechanisms for centralized college admissions, but it is also an objective in decentralized admission markets as it leads to fairer allocations.

[3]The costs of over- and underconfidence are amplified when the size of the application list is restricted; this is a standard practice in centralized assignment systems (e.g., China, Australia, Turkey, and Germany).

[4]For evidence on a gender aspiration gap, see Delaney and Devereux (2021a), Saygin (2016), and Reuben et al. (2019). For studies documenting social aspiration gaps, see Hoxby and Avery (2012); Dynarski et al. (2021); Chetty et al. (2023); Falk et al. (2020); Carlana et al. (2022); Black et al. (2015); Page and Scott-Clayton (2016); Hoxby and Avery (2012).

[5]In 2021/2022, students typically paid 170 euros per year for undergraduate courses in public universities (Campus France, 2022), and most prestigious programs (CPGE) are free.

subjects), etc.). Finally, social inequalities in college access in France are comparable to those in other developed countries, including the US (Bonneau and Grobon, 2022).

To investigate the link between confidence and college applications, we conducted a large-scale survey of high school seniors participating in the French college admission procedure in 2021. During the weeks that preceded the national deadline for college applications, we collected information on student intended application lists and student perceived admission chances in each program.[6] We also used the survey to measure students' confidence in their academic ability. To do so, we asked students about their grade point average (GPA)—a score that French students find on their school report card—and where they think their GPA ranks in the national distribution of college applicants.[7] Importantly, French students do not have this information, which forces them to guess their rank, a guess that reveals over- or underconfidence. Finally, we matched our survey data with administrative data on student college applications, the offers they receive, and the program enrolled in.

The survey data reveals that students largely misperceive their position in the GPA distribution. Students in the bottom half of the grade distribution are, on average, overconfident, while students in the top half are, on average, underconfident. Strikingly, among high-achieving students, female students are significantly more underconfident than male students. Conditional on real rank, the best female students position themselves 8.6 ranks lower in the distribution than the best males. High-achieving low-SES students are also more underconfident. Their guessed rank is 4.8 percentiles lower than that of their high-SES peers (always conditional on real rank). We do not find large gender and social differences in overconfidence among students in the bottom half of the grade distribution.

After matching survey and administrative data, we show that misconfidence strongly correlates with the prestige of the colleges students apply to and are admitted to (controlling for grades). We measure prestige as the average GPA of students attending a program. For example, being 10 percentiles less confident reduces the probability of applying to one of the elite French programs (CPGE) by 3.3 percentage points and the probability of enrolling in one by 1.6 points.[8] Given the large gender and social con-

[6]Each college offers several subjects, such as math, economics, literature, and so on. A program corresponds to a college-by-subject unit.

[7]GPA is the most important college admission criteria. The curriculum is standardized in France, which makes GPA particularly comparable across schools. In terms of admissions, the school of origin plays little role in acceptance, as we discuss in subsection 2.1 and show in Appendix C. This contrasts sharply with school-specific top percentile policies used in the US and Chile (Black et al., 2023; Bleemer, 2024; Tincani et al., 2023).

[8]In contrast, confidence does not correlate with the prestige of the "safe" choice that students make. Thus, underconfident students have less diversified application portfolios.

fidence gaps we document in the paper, these first results suggest that misconfidence might be a key driver of the well-documented social and gender aspiration gaps.

In the second part of the paper, we therefore evaluate the causal effect of a randomized intervention that makes students aware of their under- or overconfidence and corrects it. In our survey, after measuring student confidence, we randomly split students into a treated group that receives feedback on their *real* rank in the grade distribution and a control group that receives no feedback. With this intervention we want to understand whether correcting misconfidence reduces its relevance for college choice and whether it helps alleviating the gender and social gaps in college applications.

Our results reveal that correcting misconfidence significantly reduces its importance for college choice. Providing feedback on rank reduces the effect of misconfidence on the prestige of the most prestigious program to which an applicant applies (-80%), as well as the likelihood of applying (-39%) and being admitted (-72%) to an elite program (CPGE). Among students who receive feedback, conditional on ability, misconfidence no longer plays a significant role in college choice. Interestingly, rank feedback does not increase the likelihood of students dropping out of their programs at the end of the first year of college, suggesting that misconfidence does not reflect student private information on their graduation chances. These results show that misconfidence has a large causal effect on applications and admissions. Providing feedback about relative ability moves the allocation closer to stability because fewer students envy lower-performing peers who get accepted into preferred programs. The improvement stems from underconfident students who now gain admission to more preferred colleges.

We then test whether rank feedback mitigates the application gap among high-achieving students. Our intervention closes 79% of the gender gap in the prestige of the top program listed, 61% of the gender gap in applications to elite programs, and 72% of the admission gap in elite programs. While providing feedback does not significantly affect the college applications of high-achieving male students, high-achieving females apply more ambitiously when they receive feedback. This asymmetrical effect aligns with the observation that high-achieving male students exhibit less misconfidence than their female counterparts. Correcting misconfidence is equally effective in alleviating the social aspiration gap in our sample. Feedback closes 70% of the social gap in top program prestige, and it completely closes the gap in applications and admissions to an elite program (CPGE). These results show that misconfidence is a substantial behavioral barrier for equal access to college.

In the last section, we investigate the likely mechanisms behind our treatment effects. We test whether correcting misconfidence shifts students' perception of their admission chances. Recent work shows that students often have incorrect beliefs about

the probability of being admitted. Understanding where these misperceptions come from is important (Agarwal and Somaini, 2018; Kapor et al., 2020; Tincani et al., 2023; Larroucau et al., 2021; Arteaga et al., 2022). We use information on student-guessed admission chances from our survey to show, first, that higher confidence is associated with higher perceived admission chances in prestigious programs. Second, after our intervention, we asked students to guess which program they expected they would enroll in at the end of the admission process; a variable that partially captures their perceived admission chances. Our intervention makes misconfidence less relevant when students predict the prestige of their final match.

Our findings have direct policy implications. Concerns over unequal college access have spurred various policies to increase enrollment by low-SES students, including preferential admissions (Black et al., 2023; Tincani et al., 2023; Bleemer, 2024; Otero et al., 2021; Dur et al., 2018), providing information on college costs and returns (Bettinger et al., 2012; Hoxby and Turner, 2013; Bergman et al., 2019; Jensen, 2010), and financial aid (Angrist et al., 2022). We introduce a novel intervention targeting behavioral barriers (rather than financial or informational) to college access. This intervention alleviates gender and social aspiration gaps and is low cost, easy to implement, and scalable.

Our findings also inform the design of college admissions systems. In some countries, students apply to colleges *before* knowing their exam scores, while in others, applications occur *after*. Our results suggest that the latter approach, by clarifying students' position in the distribution, can reduce gender and social application gaps. Our intervention also complements recent efforts to provide students with individual feedback on admission chances (Arteaga et al., 2022; Larroucau et al., 2021). While personalized admission probabilities are the most accurate, they are often impossible to compute as they require rich data, often unavailable, on student rank, program competitiveness, and admission criteria.[9]

Related Literature Our paper complements a growing literature on the role of behavioral factors in market design (see Rees-Jones and Shorrer (2023) for an excellent recent review). Recent papers stress the importance of accounting for behavioral considerations when designing allocation mechanisms, including for school choice and college admission. Great progress has been made to uncover the role played by bounded rationality and participant inexperience (Li, 2017; Pycia and Troyan, 2023; Bó and Hakimov, 2019; Bó and Hakimov, 2024; Gonczarowski et al., 2022), individuals' expectation-based loss aversion and rank-dependent utility (Dreyfuss et al., 2022b; Meisner and von Wangenheim, 2023a; Meisner, 2023a; Dreyfuss et al., 2022a; Chen et

[9]In France, college admission criteria and their weights are not transparent, making it difficult to calculate personalized admission probabilities.

al., 2023), correlation neglect (Rees-Jones et al., forthcoming), and unknown preferences (Chen and He, 2021; Hakimov et al., 2023; Immorlica et al., 2020; Grenet et al., 2022). Less is known about the role played by confidence.[10] Our paper provides large-scale field evidence of the relevance of confidence for the design of centralized college admissions.

Our paper also contributes to a literature showing the relevance of overconfidence in a variety of contexts spanning investment decisions (Barber and Odean, 2001), acquisitions decisions by CEOs (Malmendier and Tate, 2005), labor market and retirement decisions by individuals (Oster et al., 2013; Santos-Pinto and de la Rosa, 2020), as well as political outcomes (Ortoleva and Snowberg, 2015). Overconfidence matters because it can persist, even in settings with repeated feedback (Huffman et al., 2022). It also matters because of the gender and social gaps identified in lab and field contexts (Niederle and Vesterlund, 2007; Hoxby and Turner, 2013; Buser et al., 2014; Reuben et al., 2017; Bordalo et al., 2019; Guyon and Huillery, 2020; Landaud et al., 2019; Sterling et al., 2020; Cortés et al., 2023). Yet, despite abundant correlational evidence on the association between confidence and a variety of outcomes, evidence on the causal effect of confidence is still limited and primarily based on lab studies (Dargnies et al., 2019; Barron and Gravert, 2022; Bruhin et al., 2024; Dargnies et al., 2024).[11] Our study adds to this literature by shedding light on the causal effect of confidence in a high-stakes real-world environment.

A rich literature studies the effect of ability feedback on student achievement. Using field experiments, several papers document the effect that students' knowledge of their performance and relative rank has on their effort and grades in school and university (Azmat and Iriberri, 2010; Azmat et al., 2019; Franco, 2019; Andrabi et al., 2017).[12] Similarly, Goodman (2016) and Goulas and Megalokonomou (2021) use natural experiments—the introduction and abolition of college entrance exams which give students information on their rank in the national distribution—to show that rank information increases the prestige of the universities attended by high-achieving students. Our paper complements this literature by collecting data on students' perception of their rank, which allows us to show that these perceptions are often incorrect and that they differ by gender and social background. These two findings are key to understand why rank feedback affects student college applications, and why female and low-SES students are more affected by rank feedback.

[10] A notable exception is Pan (2019).

[11] See Dargnies et al. (2019) for the effect of confidence on early job market offers, Barron and Gravert (2022) and Bruhin et al. (2024) for its effect on effort provision, and Dargnies et al. (2024) for the delegation of managerial decisions.

[12] A distinct literature looks at the effect of student rank within a class and concludes that a better within-class rank increases test scores (Murphy and Weinhardt, 2020), affects the choice of academic tracks (Delaney and Devereux, 2021b), and raises future earnings (Denning et al., 2018).

In a related paper, Tincani et al. (2023) analyze the effect of a preferential college admission program in Chile. After finding that the policy had a lower effect for students who perceived themselves as being below the school admission cutoff, the authors use a structural model to quantify the role played by student biased beliefs on the effect of the preferential college admission program. Our papers differ in terms of methodologies. We study how confidence affects college applications using a randomized intervention rather than simulations from a structural model. Interestingly, both approaches yield similar conclusions.

Also related, Bobba et al. (2024) analyze the role played by student perceived ability on their choice of high school. In contrast, we analyze college choice, a high-stake and high-choice environment particularly prone to self-censorship from students, and hence to gender and social inequalities. Because of this potential for inequalities, our paper pays particular attention to gender differences in confidence and college applications, a question that Bobba et al. (2024) does not investigate. Moreover, to analyze social inequalities in college applications, we document the effect of rank feedback on both high- and low-SES students whereas Bobba et al. (2024) estimate treatment effects on relatively disadvantaged students and rely on a structural model to extrapolate the results to a more diverse population of students.[13]

The paper is organized as follows. In Section 2, we describe the institutional context and provide descriptive evidence of application gaps from the administrative data. In Section 3, we describe the survey and administrative data. Section 4 provides evidence on confidence gaps, while Section 5 demonstrates the relevance of misconfidence for college choice. Section 6 presents the results of the experimental intervention, and Section 7 looks into potential mechanisms. Finally, we conclude in Section 8.

2 Institutional Setting

2.1 College Admission in France

Higher education in France. In France, education is compulsory from ages 3 to 15 and consists of three stages: primary school (up to age 11), middle school (collège, ages 11–15), and high school (lycée, ages 15–18). At the end of high school, students earn the baccalaureate diploma, which grants access to higher education. There are three types of high schools and corresponding baccalaureates: general (preparing for university), technological (for short-term studies), and professional (for vocational careers).

[13] Compared to Bobba et al. (2024), we also provide feedback on relative performance rather than absolute performance, and we use incentivized measures of confidence. On the other hand, Bobba et al. (2024) show what the equilibrium effect of scaling up an information intervention would be.

While all tracks can apply to higher education, differences in curricula impact college applications and admission chances. It is also more difficult for students in vocational and technical tracks to compare their grades to those of general track students. For that reason, this paper focuses on *bac général* students, who make up 83% of university enrollments and 93% of elite track entrants. In 2021, 421,000 bac général students applied to 14,600 higher education programs. Four main types of higher education institutions exist (presented in decreasing order of prestige):

- Preparatory classes for elite colleges (*classes préparatoires aux grandes écoles*, CPGE) enroll 10% of new bac général graduates and are the most prestigious educational track. These free, two-year programs prepare students for competitive *grandes écoles* entrance exams. Importantly, students who do not gain admission to a *grande école* can transition directly into the third year of public universities. Grandes écoles, such as Écoles Normales Supérieures (ENS) and École Polytechnique, offer four-year programs and can be public or private. For simplicity, we refer to CPGE as the *elite track* in this paper.[14]

- Public universities enroll 57% of *bac général* students. They deliver bachelor degrees after three years of studies.

- Applied universities and professional schools, respectively, enroll 8% and 9% of *bac général* students. They deliver vocational degrees (called DUT and BTS) after three years (for DUT) or two years (for BTS).

In 2021, the vast majority (84%) of students from the general high school track enroll in public institutions. The French state subsidizes admission fees, which reduces financial constraints for students. In 2021/2022 (the year of our intervention), a student typically paid 170 euros per year to enroll in an undergraduate course (Campus France, 2022).

College applications. During the final year of high school, students apply for higher education via a centralized platform called Parcoursup. This platform allows students to browse programs using various types of filters (according to type of institution, location, public or private status, ...).[15] Students can submit up to 10 unordered choices, and within these choices they can make up to 20 sub-choices. For example, a

[14]The wages of students who graduate from a Master's program (5 years of higher education) is on average 60% higher than the wages of students who do not attend a higher-education institution. For students who graduate from a *grande école* (most of them also require 5 years of higher education), the wage bonus increases to 81% (Dabbaghian and Péron, 2021). Moreover, Landaud and Maurin (2021) find an hourly wage premium of about 15% after graduating from a first-tier *grande école* program rather than from a less prestigious *grande école* program.

[15]See https://archive.ph/2022.02.16-200111/https://dossier.parcoursup.fr/Candidat/carte (retrieved 16/02/2022). In 2021, each program provided the following information: public or

student can apply to a science elite track in up to 20 different institutions, which would count as one choice and 20 sub-choices.[16] We refer to a higher education institution as an *institution* (e.g., Paris Sorbonne), and a subject within an institution as a *program* (e.g., Paris Sorbonne, Math).

Figure A.1 plots the number of choices that students made in 2021. The spike at 10 choices indicates that the choice limit is binding for many students. However, there are also many students who do not exhaust the limit, while others apply to more than 10 programs, using sub-choices or programs without choice limits.

We do not assume that the choices submitted by the students represent their preferred programs; instead, we assume that students chose them believing they contain the best attainable programs. Confidence is a critical factor in this selection process, making the context well-suited to investigate the influence of confidence on college applications.

Offers and rejections. To allocate students to programs, the Parcoursup clearinghouse performs a dynamic implementation of a college-proposing deferred acceptance mechanism. On offer day, the clearinghouse sends out offers to students up to the capacity of each program. Some students may receive several offers, while others do not receive any. Students with one or multiple offers have to decide whether they want to: (i) permanently accept one of the offers (and reject the others), which typically happens when a student receives an offer from their favorite program; or (ii) tentatively accept one of the offers (and reject the others), in the hope of receiving an offer from a preferred program in the future, which happens when a student receives an offer from a program which is not her favorite. Rejected offers are automatically given to the student with the next highest priority. In 2021, the first offers were sent out on May 27 and the offers/rejections ended on July 16.

Student information on own ability. In 2021, students submitted their application lists by March 11, *before* taking the centralized high school exit exam (baccalaureate) in June.[17] This means that when students submit their applications, they only know their teacher-given grades (GPA).[18] At the end of each term (a three-month

private status, fees, address, website, classes offered, admission criteria, open days, contact person, number of places available, number of candidates, and number of students admitted the previous year. In December 2024, the Ministry added information on the grades of students admitted in previous years.

[16]For some programs, the number of sub-choices is not limited (e.g., Sciences Po).

[17]Usually, the *bac* grade is a weighted average of continuous assessments and the centralized exit exam grades. In 2021, the exit exams were canceled due to Covid such that 82% of the high school grade is based on continuous evaluation (L'étudiant, 2021). However, even in other years, student application decisions and student priorities at colleges do not depend on exit exam performance.

[18]Students also know their grades in the centralized Literature exam, which takes place at the end of the second year of high school.

period), students receive a document summarizing, in each subject, their grades and grade point average (GPA). This sheet also indicates the class min, max, and mean grade in each subject. This is the only information that students have to judge their academic ability and credentials relative to their peers. Without a standardized college entrance exam to clarify their position in the ability distribution, student under- or overconfidence can have a larger effect on college applications. In the conclusion, we discuss how our "confidence-correcting" intervention might perform in systems with a universal college entrance exam.

College admission criteria. After the application deadline, programs review all the applications received and rank students. Importantly, the programs are free to decide the admission criteria they will use. Some of the most common criteria include student GPA for the last five terms of high school, student GPA in specific subjects (such as math, physics, history, ...), student grade in the centralized literature exam (which takes place in the second to last year of high school), and some measures of student cognitive and non-cognitive skills like motivation, perseverance, autonomy (which comes from an information sheet filled in by the high school teachers and the principal). Applications do not contain family demographics, or address. The diversity of criteria used by programs and the lack of transparency on the weights given to each criterion makes it hard for students to figure out their priority in each program.

Due to this uncertainty, many students use GPA as a proxy for their admission chances, an approach that is fairly accurate. The administrative data shows that GPA strongly influences how colleges rank applicants. As shown in Figure A.2, programs begin by offering admission to students with the highest GPAs before progressively extending offers to those with lower grades. This pattern is consistent across all programs. Moreover, GPA plays a large role in determining the likelihood of receiving an offer from a top program (a program in the top 10th percentile of the prestige distribution). As reported in Appendix C, the R^2 of a regression of the likelihood of receiving an offer from a top program on GPA is 0.39. The French Court of Auditors also confirmed GPA as a dominant criterion in flagship programs through machine-learning analyses of applications and admissions (Cour des Comptes, 2020).

The lack of transparency on program admission criteria has raised concerns about some prestigious programs reweighting student GPAs depending on the high schools in which they were obtained, in an attempt to account for hypothetically harsher grading standards in some prestigious high schools. We do not find evidence supporting this concern in the administrative data. To test for potential reweighting, we regress student chances of receiving an offer from one of the top programs on student GPA and the full set of high school fixed effects (see Appendix C for details). Only 7.9% of

the high school fixed effects are statistically significant at the 5% level, which suggests that reweighting is not widespread and only applied to a minority of schools. The R^2 of the regression also only moves up from 0.39 to 0.41 when we add the high school fixed effects to the specification, which further confirms that a student high school plays a limited role in their admission chances.

2.2 Application gaps by gender and socioeconomic status

A rich literature has documented aspiration gaps by gender and socioeconomic status (Chetty et al., 2023; Dynarski et al., 2021; Falk et al., 2020; Carlana et al., 2022; Black et al., 2015; Page and Scott-Clayton, 2016; Hoxby and Avery, 2012; Delaney and Devereux, 2021a; Saygin, 2016). We find similar evidence in France using administrative data on the applications reported by more than 400,000 high school students in 2021. We look at the prestige of the application list submitted by students. We define the prestige of a program as the average high school diploma grades of the students enrolled in the program. We standardize the prestige measure to have a mean of zero and a standard deviation of one. We explain in greater detail why we proxy prestige by grades of admitted students in Section 3.2.

Figure 1 shows the maximum prestige of the application list (i.e., the prestige of the "top" program) by gender and by academic achievement. The X-axis orders students from the lowest achievers who received "No honors" to the highest achievers who received the "Highest honors."[19]

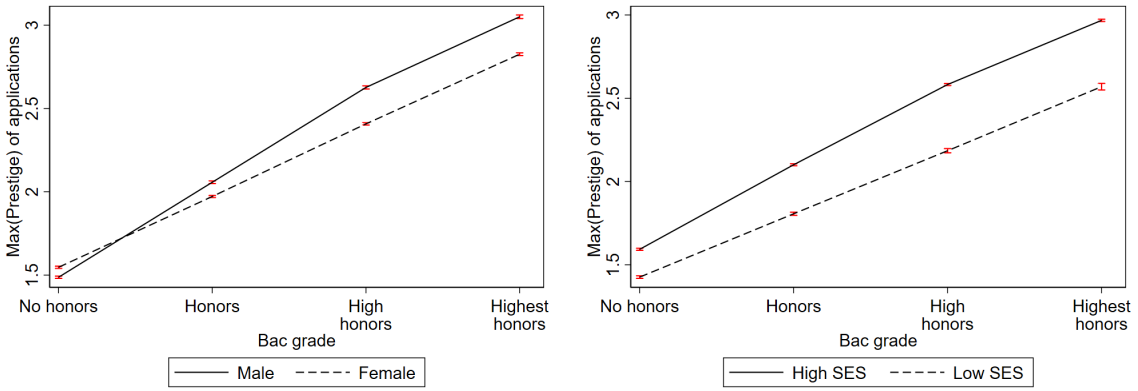
Application Gap by Gender. Large gender differences emerge in the maximum prestige of applications. Among high-achieving students, females' "top" programs are significantly less prestigious than those of males. High-achieving females are also 20.0 percentage points less likely to apply to elite programs (CPGE) and 18.5 percentage points less likely to enroll (Figures A.4a and A.4b).[20] In contrast, the gender gap in the prestige of "safe" programs is small.

Does this gap reflect private information about lower admission chances? This is unlikely, as the gender gap reverses when considering offer probabilities. Conditional on ability (honors), females are more likely than males to receive offers from their most prestigious program (Figure A.5a) and elite programs (Figure A.5c). Yet, the highest admission chances do not fully offset the lower applications. Women with the

[19]In France, baccalaureate grades translate to honors (*mention*): Among 2021 high school graduates taking part in Parcoursup, 14% earned "Highest honors" (*Très bien*), 26% earned "High honors" (*Bien*), 34% earned "With honors" (*Assez bien*), and 26% were not granted honors (*Pas de mention*).

[20]These findings align with evidence that high-achieving females are less likely to pursue highly selective colleges or high-paying professions (e.g., Boring and Brown, 2016; Delaney and Devereux, 2021a; Saygin, 2016; Reuben et al., 2019).

Figure 1: Prestige of applications by gender and socioeconomic status



(a) Max(prestige) by gender

(b) Max(prestige) by SES

Notes: These figures show the maximum prestige of the programs in students' application lists by honor and gender/SES. The prestige of a program is defined as the mean GPA (honor) of all enrolled students. Bars indicate 95% confidence intervals.

highest honors are matched to programs 0.35 SD lower in prestige compared to equally qualified men (Figure A.3a).

Application Gap by Socioeconomic Status. Significant application gaps also exist by socioeconomic status (SES). Low-SES students apply to less prestigious "top" programs, with the largest differences among high achievers (Figure 1b). High-achieving low-SES students are 14.7 percentage points less likely to include elite programs in their applications (Figure A.4c) and 10.7 percentage points less likely to enroll in one. These findings confirm prior evidence that high-achieving low-SES students disproportionately avoid prestigious academic tracks (Chetty et al., 2023; Dynarski et al., 2021; Carlana et al., 2022; Falk et al., 2020; Page and Scott-Clayton, 2016; Black et al., 2015; Hoxby and Avery, 2012).

The social gap reverses when considering offer probabilities (Figures A.5b and A.5d). Low-SES students are more likely than high-SES students to receive offers from their top programs, suggesting less ambitious applications. Despite these higher admission chances, low-SES high achievers are matched to programs 0.55 SD less prestigious than equally qualified high-SES students.

In summary, application gaps by gender and SES are most pronounced among high achievers, who are the most likely to benefit from attending prestigious colleges with higher returns (Chetty et al., 2023; Zimmerman, 2019; Anelli, 2020; Altonji et al., 2016; Kirkeboen et al., 2016; Hastings et al., 2013). While various factors may contribute to application gaps, prior research highlights systematic confidence gaps by gender and SES (e.g., Niederle and Vesterlund, 2007; Almås et al., 2016; Guyon

and Huillery, 2020; Buser et al., 2022). Our findings suggest that underconfidence contributes to these gaps: high-achieving females and low-SES students are more likely to receive offers from their top programs, implying under-ambitious application lists. In subsequent sections, we leverage survey and administrative data to explicitly examine the role of confidence in explaining these gaps.

3 Data and intervention

3.1 Survey data

Social media recruitment. We conducted a large-scale survey of students applying to college in 2021. Our target group, French high school seniors aged 17 to 18 years, is hard to reach using traditional sampling techniques (like telephone screening).[21] We therefore recruited our sample using social media ads on Instagram, Snapchat, and Facebook; an effective recruitment channel as the majority of our target group are active users.[22] We used the platforms' targeting options to show the ads to 17 to 18-year-old individuals living in France, and we targeted the ads by gender to obtain a gender-balanced sample.

Our ad (see Figure D.1 in the appendix) invited students in their final year of high school, who were about to submit their college preferences, to participate in a survey. To incentivize participation, the ad also offered participants the chance to win Amazon.fr gift cards upon survey completion. Individuals who clicked on the ad were redirected to the Qualtrics survey. Our final sample consists of 2,034 students in the general high school track, who completed the survey between February 18 and March 11, that is, in the three weeks before the deadline to submit college application lists (March 11). Appendix D details the recruitment process and the sample.

Relying on targeted social media ads to recruit hard-to-reach study participants is becoming increasingly popular in social sciences and economics (e.g., Garbiras-Díaz and Montenegro, 2022; Allcott et al., 2020; Rosenzweig et al., 2020; Samuels and Zucco, 2013). Several studies that have compared the behavior and preferences of individuals recruited through targeted social media ads and through gold-standard probabilistic sampling techniques show very similar results (Schneider and Harknett, 2022; Zhang

[21] For another project, we hired a large survey company that has more than 60,000 panelists, and we asked them to recruit the same target sample on a best-effort basis. Their job resulted in the recruitment of only 171 participants, a number that falls significantly short of what is required to execute the project presented in this study.

[22] In 2020, 89% of 16 to 18-year-olds in France used Instagram, and 82% used Snapchat (Leroux, 2020).

et al., 2020; Jäger, 2022), in particular when stratifying based on demographics, as we do in this paper.

Table A.1 shows that our sample of surveyed students is representative of the French student population in terms of age, GPA, and geographic location (see columns 1 and 2). Surveyed students are 17.5 years old on average, which is almost identical to the average age in the administrative data. 20.9% of the surveyed students live in the Ile-de-France region—the extended-Paris area— (vs. 19.5% at the national level), and respectively 23.3%, 33.9%, 27.1%, and 15.7% received no honors, some honors, the high honors, and the highest honors at the Baccalaureate (vs. 25.8%, 33.6%, 26.3%, and 14.4% at the national level). The share of girls is higher in our survey (62.0%) than at the national level (55.8%), as is the share of low-SES students (30.6% vs. 25.9%). This over-sampling of low-SES students, although not intentional, allows us to get more precise estimates of social gaps in confidence and in aspirations.

Background characteristics. Figure 2 provides an overview of the survey flow, while Appendix G describes the instructions. We started by collecting demographic information on student birth date, gender, postal code, and school name. We used these variables to match our survey data to the administrative data for students who did not provide their national student identifier (INE). We also elicited student risk preferences by asking them about their general willingness to take risk on an 11-point scale (Dohmen et al., 2011).

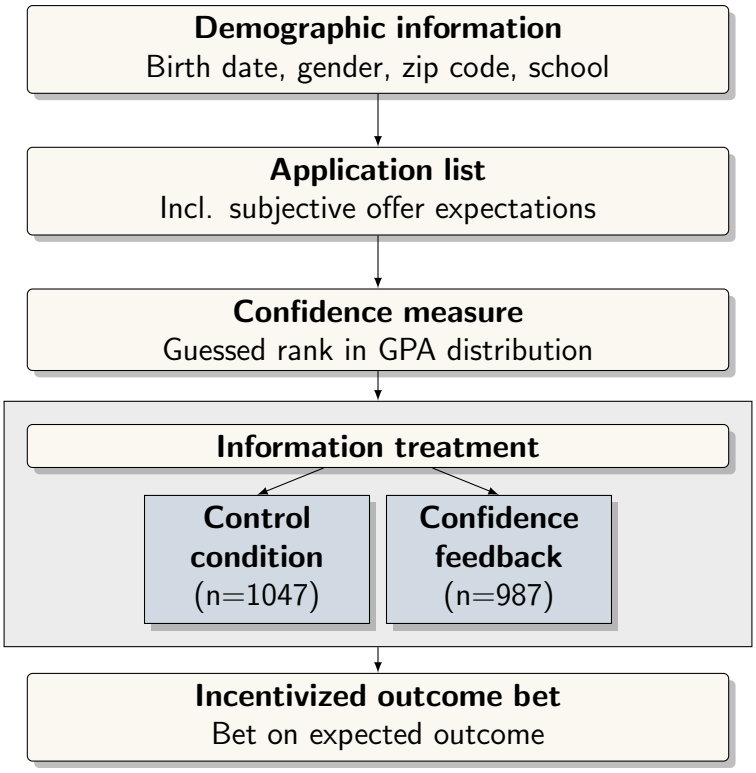
Student intended applications. We then asked students for the list of programs they were planning to apply to on Parcoursup. Students could enter between two and ten programs. For each program, we asked them to type in the city, the institution, and the program name. Finally, for each program on their list, we asked students how they evaluated the probability (in percent) of receiving an offer from that program. This question aims at measuring student beliefs about admission chances.[23]

Confidence measure. In the second part of the survey, we measure students' confidence in their academic ability. We build on a rich literature in experimental economics that has used students' beliefs about their relative performance in a group of competitors (Niederle and Vesterlund, 2007; Buser et al., 2014; Dargnies et al., 2019). In our context, we elicit student beliefs about their rank in the grade distribution. We asked students for their grade point average (GPA) in the most recent academic term.[24] GPA

[23]The survey also contained questions on students' cardinal preferences for programs, on the way students acquired information on programs, and on whether their preferences depend on the programs their peers attend. We collected this additional data for a complementary project.

[24]As discussed in Section 2.1, at the end of each term (Sept-Nov, Dec-Feb, and March-June), students receive a document summarizing their grades in each subject, and their GPA across all subjects. We asked students to report the latter GPA. When participating in our survey they had

Figure 2: Survey design



is the most salient proxy of a student's academic ability in high school, which makes it a good candidate to measure student confidence. After students entered their GPA, we elicited their beliefs about the rank of their GPA, compared to a reference sample of students in the general high school track, who will participate in the college admission mechanism. Students had to report their percentile rank on a slider from 0 to 100.[25] To encourage truthful reporting, we informed students that, among those who were correct in their belief (+/- 3 percentiles), we would randomly select ten students to receive a 100 Euro Amazon.fr gift card.[26]

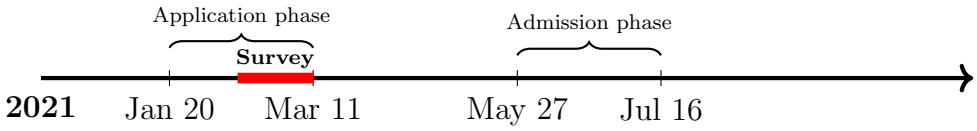
Throughout the analysis, we use two reference samples to assess whether students correctly guess their position in the distribution. The *first reference sample* consists of the universe of French students from the final year of the general high school track, who participated in the college admission mechanism. This sample is relevant as it is a salient benchmark for many students. It contains all the students with whom they will compete for a college seat. However, at the time of our survey, the administrative data

not yet received the second-term GPA, so we asked for the first-term GPA. Figure A.8 shows that self-reported GPA aligns well with the GPA observed in the administrative data.

[25]The starting position of the slider was at the 50th percentile rank.

[26]When students reported their GPA, they were unaware that they would be asked about their relative rank on the subsequent page, without the option to return to the previous one. This design feature helps reduce the potential for strategic reporting to enhance their chances of winning the gift cards.

Figure 3: Survey timing in the college admissions process



on the GPA of French students was not available.[27] We, therefore, collected our own data on the GPA of 1,001 students three weeks before our main survey. This sample forms our *second reference sample*. We refer to this first survey as "pre-survey" in the rest of the paper. This sample comprises students who (i) were in the final year of high school and in the general track (*bac général*), (ii) planned to apply to colleges in 2021, and (iii) were recruited via ads on Instagram and Facebook. We asked students about their GPA in the first term of their last year of high school; this is the same GPA that we also elicited in the main survey. We then used the 1,001 stated GPAs to compute the grade distribution, which we employed to inquire students in the main survey about their perceived position in the distribution. Importantly, we clearly explained to students in the main survey that the reference sample was composed of the 1,001 students who fulfilled the three criteria mentioned above. We consider this second reference sample to be equally relevant since using students' beliefs about their relative performance in a group of clearly-identified competitors is a common measure of individual confidence.[28]

We show in Appendix E that the characteristics of the students in the pre-survey sample are similar to the students at the national level (in the admin data) in terms of age, gender, and GPA. 57.4% of the students in the pre-survey are female (vs. 55.8% at the national level), with an average age of 17.4 years (17.5 at the national level), and an average GPA of 14.0 (13.5 at the national level).

Information treatment: Correcting over- and underconfidence. The second part of the survey aims at measuring the causal effect of student confidence on their college choices. Shedding light on this relationship requires dealing with the endogeneity of a student's confidence which might be correlated with many unobserved traits. To do so, we designed an information treatment that experimentally alters student over- or underconfidence. Just after eliciting student confidence, we randomly split the sample into a treated group (987 students) that received feedback on their correct rank in the grade distribution and a control group (1047 students) that received no

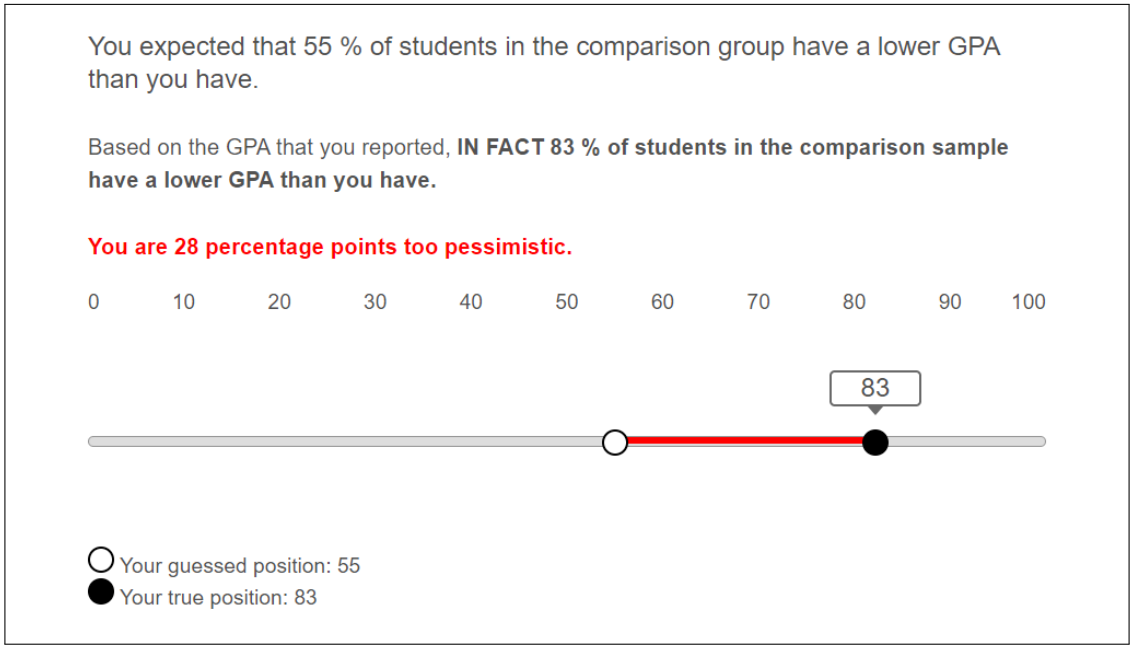
[27] The ministry only collects this information when students submit their college applications, and the data from the previous year had not been released yet.

[28] In Niederle and Vesterlund (2007), participants compare their performance to a group of three or four lab participants from the Pittsburgh Experimental Economics Laboratory. In Buser et al. (2014), students compare themselves to their school peers.

feedback. The feedback provided is simple, as illustrated in Figure 4. On a slider, we show students their guessed rank and their real rank. The gap between both illustrates the degree of their misperception.[29] An additional statement indicated: "You are X ranks too optimistic/pessimistic".[30]

To maintain consistency with the previous question on confidence, we define a student's correct rank based on the sample of 1,001 students we surveyed in the "pre-survey." In the main survey, we explicitly informed students that the feedback was based on this reference sample. Moreover, Figure A.9 shows that the rank information we would have provided using the national distribution would have been similar, especially for high-achieving students. In the rest of the analysis, we report results using both reference samples.

Figure 4: Screenshot of rank feedback



Notes: After students guessed their rank on a slider, the treatment group received feedback on their real rank on the same slider. In this example, the subject underestimated their rank by more than 10 percentiles. The instructions are translated from French.

Short-term outcome: Guess of the final match. As illustrated in Figure 3, we conducted the survey right before the application deadline, so our information treatment may have affected student college applications. To capture short-term outcomes, in the very last part of the survey (i.e., after the information treatment), we asked

[29]The treatment is similar to Hvidberg et al. (2023) who provide individuals with information on their real rank in the income distribution.

[30]To emphasize large misperceptions of rank (strong over- or underconfidence), we highlighted the gap between guessed and real rank using three colors. Gaps within three ranks were marked green for small misperceptions (Figure G.12), three to ten ranks yellow for medium misperceptions (Figure G.13), and over ten ranks red for large misperceptions (Figure 4).

students to bet on the program they expected to enroll in. They could choose one program from their submitted application list. To incentivize bets, students who correctly guessed the program had the chance to win one of twenty 50 Euro gift cards.[31]

3.2 Administrative data

Student demographic characteristics. We matched our survey data with administrative data, provided by the French Ministry of Education, on the universe of 2021 college applicants (SIES, 2022b). The data contains information on student demographic characteristics, such as gender, age, parent profession, high school, and the final high school diploma (*baccalaureate*) grade in four honors categories ("highest honors," "high honors," "honors," and "no honors"). We use the latter information on student academic level to check whether confidence and treatment effects differ for high- and low-achieving students. During the academic year we consider (2020/2021), honors were attributed based on the continuous evaluations students took during the last two years of high school.[32]

We use honors to proxy for student's academic ability since they are a salient classification in the French educational system and summarize student test scores over all terms (which makes it less prone to measurement error than the student self-reported GPA which only pertains to one term). Moreover, we match administrative data published in June 2023, which includes the term GPA that we elicit in the survey (SIES, 2023). Figure A.8 shows that self-reported GPA aligns well with the GPA in the administrative data.

We define student socioeconomic background based on parent profession. We rely on a standard classification of occupations defined by the French statistical institute (Insee, 2016).[33] Manual workers, low-skilled employees (working and retired), and the unemployed are considered to have low socioeconomic status. We classify a student

[31] We rewarded students after the end of the college admission process. We contacted 20 respondents and asked which program they had accepted. 15 of them responded, and, among those, eight indicated the program they had bet on (and received the gift card), while seven indicated a program different from their bet. Students were not aware at the time of the survey that, to determine their payout, they would be asked to self-report the final outcome. Hence, we do not expect that the basic possibility to misreport the final outcome affected the bet in the survey.

[32] Honors are usually also based on student performance in the centralized high school exit exam, but the pandemic prevented most final exams from taking place. This is why in 2020/2021 honors were attributed based on the continuous evaluations students took during the last two years of high school (French Ministry of Education, 2021). L'étudiant (2021) estimates that 82% of the general *baccalaureate* in 2021 was based on continuous evaluations.

[33] This is a widely used approach to defining students' socioeconomic background in France (see Terrier et al. (2021) and Guyon and Huillery (2020)). Insee (2016) and Insee (2020) group 42 professions into four categories: manual workers (with a monthly gross income of €2,295), low-skilled employees (€2,198), intermediate occupations (€3,095), and high-skilled occupations (€5,514).

as low SES if both parents are low SES or if one parent is low SES and the other is missing; otherwise, the student is classified as high SES.

College applications, college admissions, and program prestige. The administrative data also contains the complete list of programs students applied to, the offers they received, the response given by the student to each offer, and the final match. The data covers 17,107 programs in 4,947 institutions. As explained in Section 2.2, we define the prestige of a program as the average high school diploma grade of its students. Classifying colleges based on the academic skill of their student body—commonly measured by SAT scores and GPA in the U.S.—is a widely used approach in the literature to identify more selective (and prestigious) institutions (Black et al., 2023; Dynarski et al., 2021; MacLeod et al., 2017; Goodman et al., 2017; Hoekstra, 2009).[34]

We standardize prestige to have a mean of zero and a standard deviation of one. To calculate program prestige, we use the 2021 data and assume that our intervention did not meaningfully change the prestige of programs.[35] Figure A.7 shows the distribution of the resulting prestige index, and we discuss in Appendix B, other program characteristics like college access rate, that could be used to measure a program prestige.

College dropout. We complement the data with administrative enrollment data for universities, CPGEs and all other post-secondary tracks (e.g., SIES, 2021b, 2022c, 2021a, 2022a). These datasets allows us to study college dropout by checking whether students are still enrolled one year after they initially enrolled following their college application. We consider that an individual dropped out from a program if they switched to a different institution or if they switched to a different university program within a university.[36]

[34]Extensive research suggests that enrolling in a college with higher peer quality is associated with greater returns (Black et al., 2023; Bleemer, 2024; Zimmerman, 2019; Anelli, 2020; Altonji et al., 2016; Kirkeboen et al., 2016; Hastings et al., 2013) and stronger student preferences. In our sample, students systematically rank more prestigious colleges higher on their application lists, with average prestige declining further down their rank order (See Figure A.6).

[35]Using 2020 data yields prestige scores that are highly correlated (r=0.930) with those based on 2021 data for the programs the survey students apply to. However, with the 2020 data, we are unable to calculate the prestige of more than 12% of the 2021 programs that were not available in 2020.

[36]We exclude program-switchers who were enrolled in a multidisciplinary study program in the first year, in which specialization after the first year is part of the curriculum. Moreover, we do not include students who switch to medicine since many programs offer access to a medical degree as part of the curriculum (*license access santé*).

4 Evidence on confidence gaps

4.1 Confidence gaps by gender and SES

Gender confidence gap. Figure 5 plots individuals' beliefs about their rank in the GPA distribution (Y-axis) as a function of their high school diploma grade (x-axis). The higher the rank on the Y-axis, the higher they believe they are in the GPA distribution. We find large confidence gaps between male and female students at the top of the distribution. In contrast, there are only small gender differences in confidence for students who obtain "No honors" or "Honors." Figure A.10 shows a fuller picture of confidence gaps along the distribution by plotting the guessed GPA rank against the real GPA rank, which we calculated using the reference sample. In the bottom half of the grade distribution, males and females are all significantly overconfident, without large gender differences. In contrast, in the top half of the grade distribution, male and female students are all significantly underconfident, though female students are notably more underconfident than male students.[37]

To quantify the confidence gap, we construct the variable Misconfidence, which corresponds to the difference between student i's guessed ability rank and their real rank:

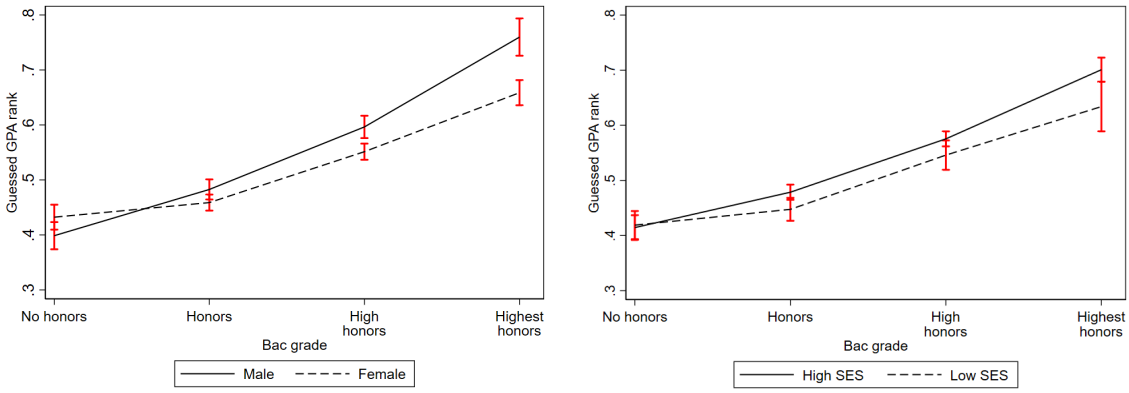
$$\text{Misconfidence}_i = \text{Guessed rank}_i - \text{Real rank}_i, \tag{1}$$

This variable is positive for overconfident students who guess a higher rank than their real rank, and negative for underconfident students who guess a rank lower than their real rank. An increasing value of the misconfidence variable always corresponds to a higher confidence: For students who are overconfident, increasing misconfidence means that students become more overconfident. For students who are underconfident, increasing misconfidence means that students become less underconfident. We scale the variable to range between -1 to 1. We plot the distribution of misconfidence in Figure A.11.

To investigate whether misconfidence is driven by under- or overconfident students, we construct two additional variables. Underconfidence_i is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). The larger this variable, the more underconfident a student is. Conversely, Overconfidence_i is equal to the

[37] Student underconfidence at the top of the distribution and overconfidence at the bottom are partly mechanical due to mean reversion: the worst students can only weakly overestimate their rank, while the best students can only underestimate their rank. Thus, misconfidence is negatively correlated with true ability. To control for this in a flexible way, we systematically control for student real rank in regressions and we control for honors fixed effects.

Figure 5: Guessed GPA rank by gender and SES



(a) Guessed rank by gender

(b) Guessed rank by SES

Notes: This figure shows the average guessed GPA rank by a student honors. Panel (a) reports gender differences in guessed GPA, while panel (b) reports social differences in guessed GPA. Bars indicate 95% confidence intervals. Figure A.10 in the appendix plots students' guessed GPA rank (y-axis) against their real rank (x-axis).

difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). The larger this variable, the more overconfident a student is.

In Table 1, we regress the variable misconfidence on a female dummy variable, controlling for student real rank at the national level (from the administrative data). The results show that female students are 1.7 percentage points less confident than male students on average—i.e., conditional on real rank, they perceive themselves as 1.7 ranks lower in the GPA distribution—and 3.6 percentage points less confident when considering underconfident students only. The gender gap widens sharply among high-achieving students. For students with the highest honors, female students are 8.6 percentage points less confident than male students, with most of this difference being driven by underconfident students. Table A.3 shows that these results look very similar when using the GPAs of the pre-survey sample as the reference sample.

Social confidence gap. Figure 5 shows a very similar confidence gap by socioeconomic status. While high-SES and low-SES students are equally overconfident at the bottom of the GPA distribution, there is a large underconfidence gap between low-SES and high-SES students at the top of the distribution. This finding is also supported by Figure A.10b in the appendix, in which we plot students' guessed GPA rank (y-axis) against their real rank (x-axis). Low-SES students are, on average, 2.0 percentage points less confident, which is mostly driven by underconfident students (see Panel B of Table 1). Once more, the confidence gap is larger among high-achieving students.

Table 1: Confidence gaps by gender and social background

	Misconfidence	Underconfidence	Overconfidence
		Panel A: Gender gap	
All students	-0.017**	0.036***	0.019**
	(0.007)	(0.008)	(0.010)
	[2034]	[1147]	[857]
Students with ...			
... no honors	0.037**	0.002	0.043**
	(0.016)	(0.019)	(0.017)
	[473]	[70]	[397]
... honors	-0.020*	0.013	-0.003
	(0.011)	(0.012)	(0.013)
	[690]	[316]	[363]
... high honors	-0.036***	0.036***	0.018
	(0.012)	(0.012)	(0.012)
	[552]	[448]	[91]
... highest honors	-0.086***	0.077***	-0.023
	(0.019)	(0.019)	(0.059)
	[319]	[313]	[6]
		Panel B: Social gap	
All students	-0.020**	0.034***	0.012
	(0.008)	(0.009)	(0.010)
	[2000]	[1128]	[842]
Students with ...			
... no honors	0.008	0.000	0.011
	(0.017)	(0.019)	(0.017)
	[462]	[70]	[386]
... honors	-0.026**	0.028**	0.017
	(0.013)	(0.012)	(0.014)
	[680]	[310]	[359]
... high honors	-0.028**	0.032**	-0.013
	(0.014)	(0.015)	(0.014)
	[544]	[440]	[91]
... highest honors	-0.048**	0.052**	0.085
	(0.024)	(0.023)	(0.066)
	[314]	[308]	[6]
Real rank (admin)	✓	✓	✓

Notes: This table reports the coefficients from separate regressions of misconfidence (column 1), underconfidence (column 2), and overconfidence (column 3) on a binary variable for female students (Panel A) and a binary variable for low-SES students (Panel B). Misconfidence corresponds to the difference between a student guessed ability rank and their real rank. This variable ranges between -1 to 1. Underconfidence is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). Overconfidence is equal to the difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). All regressions control for a student real rank. Confidence measures are defined using the national GPA distribution. After running regressions on the full sample (top coefficient in each panel), we divide the sample by four honors categories which are mutually exclusive. We report robust standard errors in round parentheses and the number of observations in square brackets. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

For students with the highest honors, low-SES students are 4.8 percentage points less confident than high-SES students, with most of this difference being driven by underconfident students.

4.2 Sources of misconfidence and confidence gaps

Why do students misperceive their position in the national GPA distribution? In our setting, because students are informed every term of their GPA in each subject, along with the lowest and highest grade of their class peers, they have a reasonable perception of their within-class and within-school relative performance.[38] Students may anchor their beliefs about their national rank to their school rank (Jäger et al., 2024).[39] If high-achieving students are clustered in top schools and low-achieving students in weaker schools, anchoring could explain the pattern of misconfidence we observe: underconfidence among high achievers and overconfidence among low achievers. Differences in school composition could also contribute to gender and social gaps in confidence if high-achieving female (or low-SES) students in top schools enroll with higher-achieving peers than male (or low-SES) students.

To test whether school rank anchoring contributes to incorrect rank beliefs, we examine the gap between school and national rank across the GPA distribution by gender and SES. Figure A.12 reveals three findings. First, Low-achievers ("No honors") have higher school ranks than national ranks, while the reverse holds for high-achievers ("Highest honors"), suggesting school rank anchoring explains some overconfidence in low achievers and underconfidence in high achievers. However, the next two results rule out the fact that school rank anchoring explains gender and social confidence gaps:

1. Figure A.12a shows no gender difference in school-to-national rank gaps, particularly among high achievers, indicating school rank anchoring does not explain gender gaps in beliefs.
2. Figure A.12b shows no social difference in rank gaps among high-achievers. While low-SES students generally have higher school ranks than national ranks, this difference disappears for high-achievers. Low-SES students likely adjust their within-school rank downward when estimating national rank, avoiding overconfidence.[40]

To confirm that school ranks do not drive gender and social confidence gaps, we test whether the gaps disappear when comparing students' beliefs against their school

[38] Class rank approximates school rank as most final-year classes are electives, mixing students across classes.

[39] Jäger et al. (2024) show that workers anchor their salary expectations to their current firm levels.

[40] For low-achievers, the lack of a social confidence gap, despite higher school ranks, suggests low-SES students do not anchor national rank beliefs to school rank. Instead, they adjust ranks downward when estimating national rank.

GPA distribution. More specifically, we redefine misconfidence as Guessed rank$_i$ − Real *school* rank$_i$, and we regress misconfidence on gender and SES, as we did in Table 1. The results, reported in Table A.4 are nearly identical to those in Table 1, confirming that anchoring does not explain gender or social confidence gaps. Instead, gaps arise when students try to guess their national rank based on their school rank, with high-achieving female and low-SES students correcting their school ranks downward more than male and high-SES peers, generating the observed confidence gaps.

5 Misconfidence and college choice

Outcomes. We investigate next whether confidence is associated with student college applications and admissions. Starting with the prestige of the application lists, we compute (i) the minimum prestige of all the applications, which we refer to as the "safe" program, (2) the maximum prestige of the applications, which we refer to as the "top" program, and (3) the average prestige of the application list. In addition, we assess whether a student applies to at least one elite program (CPGE); an important outcome as *grandes écoles* in France lead to higher paying jobs and prestigious positions (cf. Section 2.1). Second, we consider the prestige of the final match, which corresponds to the prestige of the program a student ultimately enrolls in, and whether a student enrolls in an elite program.

Estimation strategy. To estimate whether misconfidence is associated with college applications and admissions, we use the following specification:

$$\text{Y}_i = \alpha_0 + \alpha_1 \text{Misconfidence}_i + \alpha_2 \text{Real rank}_i + \alpha_3 X_i + \epsilon_i \quad (2)$$

Y_i are the outcomes described above. Misconfidence$_i$ corresponds to the difference between a student's guessed ability rank and the real rank, as defined in Equation (1). The larger this variable, the more overconfident (and the less underconfident) a student is. Importantly, by controlling for the real rank of a student, α_1 measures the association between misconfidence and our outcomes, keeping the real rank constant. By controlling for real rank, the variation in misconfidence is driven by variation in the guessed rank. We include indicators of a student's honors to control for academic ability more flexibly[41] and we control for risk preferences (Dohmen et al., 2011).[42]

[41] The impact of a student real rank on the outcomes may be non-linear. We control for bac honors fixed effects to allow for differing intercepts. Interacting the *bac* honors fixed effects with the real rank gives similar results for the coefficients of interest.

[42] Some students may view applying to a CPGE as risky. These two-year programs prepare students for competitive Grande École exams, but those failing able to enter the third year of university. If some students are unaware of these fallback options, they might perceive choosing a CPGE as risky.

Table 2: Association between misconfidence and college applications and admissions

	College Applications				College Admissions	
	Max Prestige (1)	Min Prestige (2)	Mean Prestige (3)	One CPGE (4)	Prestige (5)	CPGE (6)
Panel A: Effect of misconfidence						
Misconfidence	0.716***	0.119	0.495***	0.330***	0.474**	0.160***
	(0.200)	(0.094)	(0.139)	(0.076)	(0.188)	(0.056)
Panel B: Effect of under- and overconfidence						
Underconfidence	-0.681**	-0.324**	-0.667***	-0.526***	-0.553*	-0.246***
	(0.277)	(0.155)	(0.233)	(0.129)	(0.300)	(0.090)
Overconfidence	0.754**	-0.107	0.305*	0.114	0.372	0.049
	(0.316)	(0.122)	(0.174)	(0.081)	(0.230)	(0.046)
Real rank (admin)	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Observations	1047	1047	1047	1047	914	914
Mean outcome	2.290	-0.520	0.873	0.271	0.719	0.091

Notes: This table reports the association between student misconfidence and their applications and admissions. Misconfidence is the difference between the guessed rank and the real rank. This variable ranges between -1 to 1. A student's real rank corresponds to their rank at the national level, using the GPA distribution from the administrative data. See Table A.6 for corresponding results using the GPA distribution from the pre-survey sample. Underconfidence is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). The larger this variable, the more underconfident a student is. Overconfidence is equal to the difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). The larger this variable, the more overconfident a student is. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE). The sample includes students from the control group. Robust standard errors are reported in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

We run all regressions on students in the control group to ensure that the outcome variables are unaffected by the treatment.

Results Table 2 reports the association between student misconfidence and their applications and admissions. Panel A shows that, holding ability constant, more confident students apply to more prestigious top programs (Max Prestige), and the magnitude of the association is large. Being ten percentiles more confident is associated with a 0.07 SD higher prestige of the top program and a 3.3 percentage points higher probability of applying to an elite program (CPGE).[43] To put this effect size into perspective, being ten percentiles more confident is slightly larger than the gender gap among top students (8.3 percentiles). Interestingly, misconfidence is not associated

[43]The misconfidence variable ranges from -1 to 1. The coefficients report the effect of moving from well-calibrated confidence (misconfidence = 0) to maximum overconfidence (misconfidence = 1). Dividing the coefficient by 10 indicates the effect of becoming 0.1 (10 percentiles) more confident.

with the prestige of the "safe" program (see Min Prestige). Students who overestimate their overall admission chances are not more likely to skip safe options. We then show a similar positive association between confidence on college admissions. Controlling for grades, being ten percentiles more confident, raises the prestige of the final match by 0.05 SD, and the likelihood of enrolling in a CPGE by 1.6 percentage points.

We examine whether the link between confidence and college applications is primarily influenced by underconfident or overconfident students. In Panel B of Table 2, we substitute misconfidence with underconfidence and overconfidence. Both correlate with the prestige of the applications. Underconfidence affects the likelihood of applying to an elite track (CPGE) more than overconfidence does. Being 10 percentiles more underconfident lowers the chances of applying to a CPGE by 5.3 points, whereas being 10 percentiles more overconfident "only" raises these chances by 1.1 points. This asymmetric effect is not surprising given that only the best students apply to CPGE, and these high-achieving students are precisely those suffering from larger underconfidence. The same asymmetric effect applies to college admissions. Underconfidence is associated with 2.5 points lower admission chances to elite programs (CPGE), while overconfidence is not associated with CPGE admission chances. The results are very similar when we use the GPA distribution from the pre-survey sample to define a student real rank (Panel A of Table A.6).

When discussing student applications, we noted that gender and social gaps are unlikely to reflect private information held by women and low-SES students about lower admission chances, given that these gaps reverse when examining offer probabilities. We further rule out the private information hypothesis by showing that, controlling for true ability, misconfidence is uncorrelated with the likelihood of receiving an offer (see Table A.5). Misconfidence reflects errors in self-perception rather than student information about admission chances beyond GPA rank.

Although suggestive of a strong relationship between confidence and college choice, our findings cannot yet be interpreted as a causal effect. In the next section, we use our randomized intervention to show that the relationship between misconfidence and college applications is causal.

6 Effect of correcting misconfidence on college choices

6.1 Misconfidence no longer matters after rank feedback

Estimation strategy. We investigate whether correcting students' misconfidence by providing feedback on their real rank in the ability distribution has a causal effect

on their college applications.[44] To measure the effect of correcting misconfidence, we randomly allocated students to either a treated group that received feedback on their correct rank in the grade distribution or a control group that received no feedback. Table A.1 in the appendix shows that student demographic characteristics are balanced between the 1,047 students in the control group and the 987 students in the treatment group. One exception is the share of students with the highest honor, which is slightly higher in the control group. To address this, we control for honors fixed effects in all regressions. Moreover, Table A.2 shows that the application behavior in the control group is comparable to the application behavior in the administrative data.

We use the following specification to estimate the causal effect of correcting misconfidence on college choice:

$$\begin{aligned} \text{Y}_i = &\beta_0 + \beta_1 \text{Misconfidence}_i + \beta_2 \text{Feedback}_i \times \text{Misconfidence}_i \\ &+ \beta_3 \text{Feedback}_i + \beta_4 \text{Real rank}_i + \beta_5 X_i + \epsilon_i, \end{aligned} \tag{3}$$

Y_i is the outcome. Feedback_i is a dummy variable that is equal to one for the group of students who received information on their real rank in the GPA distribution. Feedback_i is equal to zero for students in the control group. Misconfidence_i is the difference between a student's guessed and real rank, as defined in Equation (1). All regressions control for a student's real rank. β_1 measures how much misconfidence affects college choice, conditional on ability, for students who do not receive feedback. β_2 measures the impact of feedback on the influence of misconfidence in college application decisions. Moreover, β_3 estimates the effect of providing feedback for students who are neither overconfident nor underconfident as they correctly guessed their rank. X_i includes honors fixed effects to control for ability differences more flexibly, as well as controls for risk preferences. When informing students on their rank, we used the GPA distribution from the sample of students in the pre-survey. For consistency, we define the misconfidence and real rank variables using the same distribution.[45]

[44] We pre-registered the experimental intervention and the main hypotheses in the AEA RCT Registry, project number AEARCRT-0007218. As described in the pre-registration, the survey had two treatment interventions. The second treatment provided advice on strategic behavior in the Parcoursup mechanism. The results of the second treatment will be reported in a separate paper, which focuses on students' strategies. In contrast, this paper mostly focuses on application behavior before the mechanism starts. We focus on slightly different outcomes compared to the pre-registration. Instead of measuring the quality of a program by the access rates we decided to use the more precise "prestige" measure. In Appendix B, we explain why the prestige measure is better suited and show results using access rate as an alternative outcome variable. Also, in the interest of space, we skip some pre-registered outcomes in the main text and report them in Appendix F.

[45] In Table A.8, we use the reference sample from the administrative data instead and find equivalent results to Table 3.

Table 3: Effect of rank feedback on college applications, admissions, and dropout

	College Applications				College Admissions		Dropout
	Max Prestige	Min Prestige	Mean Prestige	One CPGE	Prestige	CPGE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Misconfidence	0.613***	0.101	0.422***	0.272***	0.426***	0.147***	0.014
	(0.167)	(0.080)	(0.117)	(0.065)	(0.160)	(0.046)	(0.085)
Rank feedback	0.052	0.007	0.037	-0.010	0.002	0.025	-0.007
	(0.044)	(0.024)	(0.034)	(0.019)	(0.045)	(0.015)	(0.022)
Rank feedback	-0.491***	-0.024	-0.258**	-0.105	-0.104	-0.107**	-0.009
× Misconfidence	(0.179)	(0.085)	(0.127)	(0.069)	(0.176)	(0.054)	(0.092)
Constant	1.399***	-0.812***	0.078	-0.056**	-0.544***	-0.065***	0.440***
	(0.076)	(0.035)	(0.049)	(0.025)	(0.064)	(0.018)	(0.041)
Real rank	✓	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Adj. R2	0.226	0.119	0.335	0.198	0.464	0.102	0.030
Observations	2034	2034	2034	2034	1793	1793	1696
Mean outcome	2.292	-0.521	0.874	0.260	0.691	0.098	0.302

Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the role played by confidence in student college applications, admissions, and dropout. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability distribution. Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. We define the misconfidence and real rank variables using the GPA distribution from the sample of students in the pre-survey. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE); in Column (7) an indicator of whether a student did not re-enroll in the same program after the first year. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

Effect of rank feedback. Table 3 reports the effect of rank feedback on student college applications (columns 1 to 4) and on the college they enroll in (columns 5 and 6). The top coefficient shows that, for students who do not receive feedback on their rank, being more confident leads to more ambitious applications and more prestigious admissions, controlling for true ability. The second coefficient (Rank feedback) shows that rank feedback has no effect on students who are neither overconfident nor underconfident (i.e., students who correctly guessed their rank in the ability distribution).

The story is completely different for students who are initially overconfident or underconfident (as shown by the coefficient on Rank Feedback × Misconfidence). For them, correcting the initial misconfidence significantly reduces how much misconfidence matters for college choice. Without feedback, a student who overestimates their rank by 10 percentiles applies to a top program that is 0.06 SD more prestigious. Providing feedback reduces this boosting effect by 0.05 SD, to the point that misconfidence becomes irrelevant for college choice. Similarly, feedback reduces the role played by misconfidence in the likelihood of applying (-39%) and being admitted (-73%) to an elite program (CPGE).[46] To further show that misconfidence becomes irrelevant for college choices among treated students, Table A.6 reports the correlation between misconfidence and college applications, separately for students in the control and treatment group. In the latter group, misconfidence no longer plays a role in college applications (see Panel B). This conclusion carries over to all the outcomes we consider.

Effect of rank feedback for overconfident and underconfident students. There are three reasons to examine these heterogenous treatment effects. First, we aim to understand whether informing students about their overconfidence makes them revise their applications to less prestigious programs, potentially at the cost of lowering their admission chances in prestigious programs. The results reported in Table A.7 (Panel B) show that, although correcting student overconfidence lowers the prestige of their most prestigious applications, this has no effect on the prestige of the program they ultimately enroll in. In other words, without feedback, overconfident students apply to unattainable programs, so not applying to these does not change the prestige of the final match.

Second, does informing underconfident students make them revise their applications toward more prestigious programs, potentially at the cost of no longer including

[46]The treatment closes the gap in admissions to a larger extent than the gap in applications. This could be driven by treated students behaving differently when receiving offers in the dynamic mechanism. In Appendix F.1 we show that underconfident students are more likely to accept an early offer, and that the treatment makes them more likely to accept a later offer (which tends to be of higher quality). However, the treatment effect is not statistically significant ($p = 0.168$).

safe programs in their list? We noticed earlier that students' over- and underconfidence is not associated with the prestige of their safe choice. Consistent with this finding, rank feedback has no effect on the role played by confidence on the prestige of student safe choice. Correcting underconfidence does not reduce applications to safe programs.

Finally, are underconfident students more sensitive to rank feedback than overconfident students when it comes to applications to prestigious programs? We expect so as high-achieving students are both more likely to apply to prestigious programs and they are overrepresented among underconfident students. Indeed, informing underconfident students has a larger effect on their likelihood of applying to an elite program (CPGE) and of being admitted to one than informing overconfident students (Table A.7). This result prompts an important questions: If increasing the confidence of underconfident students leads to more applications and admissions to prestigious programs, could it also create mismatches and increase college dropout rates?

Effect of rank feedback on dropout from college. Could student confidence reflect private insights about their potential for success in college? If this were true, rank feedback, by encouraging underconfident students to apply to and gain admission in more prestigious programs, could lead to mismatches and higher dropout rates.[47] To test this, we examine whether rank feedback affects the likelihood that a student does not remain enrolled in the same program during their second year of college.[48] We use a broad definition of program dropout that includes students who completely leave higher education during their second year, as well as those who switch programs (either within or outside their university) or transfer to a different university, whether or not they remain in the same field of study. The results, reported in the last column of Table 3 do not support the mismatch hypothesis. Confidence is not associated with dropout rates in the control group, and, importantly, rank feedback does not increase the likelihood of students dropping out of their programs.

6.2 Rank feedback reduces social and gender gaps in applications

Our results so far show that informing underconfident students about their rank in the ability distribution leads to more applications and admissions to prestigious programs.

[47] Changing program is common in France. 32% of our sample changed program after the first year. For recent evidence on mismatch see Bleemer (2024, 2022); Black et al. (2023); Arcidiacono and Lovenheim (2016) and Dillon and Smith (2020).

[48] We cannot look at graduation because most students in our survey graduated in summer 2024 (three years after enrollment), and it takes at least a year for the administrative data to become available. Among the 1,793 students who accepted an offer from a program in 2021, 1,696 appear in the 2021/2022 enrollment data. Some students who accepted an offer may have ultimately decided to study abroad.

Does this mean that rank feedback helps close the gender and social application gaps we document in section 4.1 among high-achieving students? To address this question, we focus next on students who received the highest honors.[49] For the great majority of these students (92%), rank feedback informs them that their GPA rank is better than they thought. Moreover, we documented that among high-achieving students, female and low-SES students are significantly less confident than their male and high-SES peers. Providing feedback may have the greatest impact on them.

Estimation strategy. To test whether rank feedback helps close the gender and social gap, we use the following specifications:

$$\begin{aligned} \text{Y}_i =& \gamma_0 + \gamma_1 \text{Feedback}_i \times \text{Female}_i \\ &+ \gamma_2 \text{Feedback}_i + \gamma_3 \text{Female}_i + \gamma_4 X_i + \epsilon_i, \end{aligned} \tag{4}$$

and

$$\begin{aligned} \text{Y}_i =& \gamma_0 + \gamma_1 \text{Feedback}_i \times \text{Low-SES}_i \\ &+ \gamma_2 \text{Feedback}_i + \gamma_3 \text{Low-SES}_i + \gamma_4 X_i + \epsilon_i. \end{aligned} \tag{5}$$

Feedback_i is a dummy variable equal to one for the randomly-selected group of students who receive information on their real rank in the ability distribution. Feedback_i is equal to zero for students who do not receive feedback. Low-SES_i and Female_i are dummy variables indicating whether a student is from a low socio-economic background and female, respectively. X_i is a vector of control variables including real rank and risk preferences. γ_2 estimates the treatment effect for males (in Eq 4) and for high-SES students (in Eq 5). We are interested in the coefficient γ_1, which estimates the differential effect of providing rank feedback for female students compared to male students (in Eq 4) and for low-SES students compared to high-SES students (in Eq 5). We run these regressions on the sample of students who received the highest honors.

Effect of rank feedback on gender gap in college applications. Rank feedback helps to close the gender gap in college applications. The results, reported in Table 4, reveal larger treatment effects for high-achieving females than for high-achieving males. The former apply more ambitiously when given feedback, whereas high-achieving males are mostly unaffected.[50] As a result, rank feedback closes 79% of the gender gap in the prestige of the best application among high-achieving students.

[49] We did not specify the focus on highest honors students in the pre-registration as we did not expect most of the gender and social gaps in confidence and in applications to come from high-achieving students. Our findings in the first part of the paper motivate the analysis in this section.

[50] Although high-achieving male students mostly receive positive information on their rank, we find no treatment effects for them.

Table 4: Effect of rank feedback on gender and social gaps in college applications, admissions, and dropout among high-achieving students

	College Applications				College Admissions		Dropout
	Max Prestige (1)	Min Prestige (2)	Mean Prestige (3)	One CPGE (4)	Prestige (5)	CPGE (6)	(7)
			Panel A: Gender gaps				
Female	-0.500***	-0.099	-0.535***	-0.327***	-0.439***	-0.283***	0.097
	(0.086)	(0.126)	(0.123)	(0.065)	(0.168)	(0.080)	(0.064)
Rank feedback	-0.079	-0.042	-0.229*	-0.120	-0.145	-0.066	-0.059
	(0.067)	(0.149)	(0.139)	(0.078)	(0.205)	(0.105)	(0.064)
Rank feedback × Female	0.398***	0.034	0.452***	0.200*	0.364	0.205*	0.035
	(0.118)	(0.170)	(0.174)	(0.102)	(0.262)	(0.120)	(0.087)
Constant	2.148***	-0.764***	0.427	0.165	-0.475	0.139	0.278
	(0.463)	(0.230)	(0.434)	(0.217)	(0.824)	(0.210)	(0.229)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Adj. R2	0.152	0.011	0.157	0.088	0.101	0.050	0.013
Observations	320	320	320	320	298	298	295
Mean outcome	3.156	-0.203	1.787	0.631	2.125	0.275	0.186
			Panel B: Social gaps				
Low-SES	-0.637***	-0.265**	-0.687***	-0.301***	-0.824***	-0.226***	-0.066
	(0.185)	(0.115)	(0.154)	(0.088)	(0.228)	(0.056)	(0.073)
Rank feedback	0.111	-0.035	0.043	-0.038	0.013	0.042	-0.061
	(0.071)	(0.080)	(0.091)	(0.059)	(0.138)	(0.062)	(0.051)
Rank feedback × Low-SES	0.450**	-0.002	0.137	0.322**	0.302	0.214*	0.090
	(0.225)	(0.146)	(0.210)	(0.141)	(0.362)	(0.123)	(0.119)
Constant	1.956***	-0.737***	0.239	0.021	-0.532	-0.016	0.442*
	(0.406)	(0.239)	(0.395)	(0.219)	(0.802)	(0.213)	(0.229)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Adj. R2	0.179	0.034	0.201	0.066	0.146	0.027	-0.005
Observations	315	315	315	315	294	294	291
Mean outcome	3.158	-0.201	1.790	0.635	2.125	0.279	0.186

Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the gender gap (panel A) and social gap (panel B) in college applications, admissions, and dropout. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who receive information on their real rank in the ability distribution. Low-SES and Female are dummy variables indicating whether a student is from a low socio-economic background and female, respectively. We run these regressions on the sample of students who received the highest honors. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE); in Column (7) an indicator of whether a student did not re-enroll in the same program after the first year. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

To go beyond average treatment effects, Figure A.13 plots the maximum prestige distribution, separately for the treatment and control group. The treatment effect is driven by a reduction in the share of high-achieving female students who do not apply to any prestigious program. In contrast, high-achieving male students already apply to very prestigious programs in the control group.

Rank feedback also closes 61% of the gender gap in the likelihood of application to an elite program and 72% of the gender gap in admissions to elite programs. Feedback increases women's admissions to elite programs by 13.9 percentage points. All in all, these results show that informing high-achieving female students that their GPA rank is at the top of the distribution has a larger effect on them than on high-achieving male students, which reduces the application and admissions gap. Importantly, the treatment has not increased dropout among female students, suggesting that it did not increase mismatch.[51]

Effect of rank feedback on social gap in college applications. We reach similar conclusions on the effect of rank feedback on the social application gap. Panel B of Table 4 reports treatment effects for high-SES and low-SES students. Once again, rank feedback has a larger effect for high-achieving low-SES students than for high-achieving high-SES students, so that rank feedback closes 71% of the social gap in the top program prestige. Figure A.13 shows that this treatment effect is mostly driven by a reduction of non-prestigious top choices among low-SES students. Rank information also entirely closes the social gap in applications and it closes 95% of the social gap in admission to an elite program (CPGE). Overall, we observe substantial effects on high-achieving female and low-SES students, indicating that a simple intervention can effectively reduce gender and social gaps in college admissions.

7 Mechanisms: Perceived admission chances vs. perceived success in college

In this section, we use our survey data to explore two channels through which confidence can influence college choice: students' perceptions of their admission chances and their perceptions of their potential success in a program.

Perceived admission chances. We exploit a survey question asking students how they evaluate the probability (in percent) of receiving an offer from each program they have listed. We refer to this outcome as "Offer belief." This question being

[51]For completeness, Table A.9 reports the results for students who did not obtain the highest honors. For these students, the rank feedback reduced the gender gap to a lesser extent and not significantly so.

asked before the randomized intervention, we use offer beliefs as a pre-determined student characteristic.[52] We examine student overall beliefs about admission chances (i.e., across all programs they applied to), but also their beliefs regarding prestigious programs, i.e., (i) programs in the top 10% of the prestige distribution and (ii) elite programs (CPGE). Misperception about prestigious programs can be particularly costly, especially among high-achieving students.

To examine the relationship between misconfidence and perceived admission chances, we use a similar specification as in Section 5, Equation (2):

$$\mathrm{Y}_{ij} = \beta_0 + \beta_1 \text{Misconfidence}_i + \beta_2 \text{Real rank}_i + \beta_3 X_i + \beta_4 W_j + \epsilon_{ij},$$

Observations are at the student-program level. Y_{ij} measures student i's belief that they will receive an offer from program j. More confident students may apply to more competitive programs with lower admission chances, which could bias the estimate of β_1. To avoid this, W_j includes controls for the prestige of the programs a student applies to (both linearly and using a quadratic term). All regressions also control for student real rank and honor fixed effects.

Table 5 reports the results on the association between student misconfidence and their beliefs about their chances of receiving an offer, controlling for ability and program prestige. A 10 percentile higher confidence increases a student's belief that they will receive an offer from a program by 7.0 percentage points.[53] For the most prestigious programs, confidence plays an even larger role in perceived admission chances. A 10 percentile higher confidence increases a student's belief that they will receive an offer from one of the top 10% most prestigious programs by 10.3 percentage points, and from an elite program by 14 points.

Perceived chances of success in a program. To shed light on the second channel, we leverage the fact that, when students receive an offer from a prestigious program, they may be more inclined to accept the offer if they are confident that they can succeed in the program. We therefore examine whether the likelihood of accepting a prestigious offer (from a program in the top 10% of the prestige distribution or from an elite program) is correlated with misconfidence. In Table A.10, we find no relationship between misconfidence and acceptance. Both coefficients are insignificant and close to zero.

Overall, our findings primarily support the first mechanism—a change in student perceived admission chances— rather than the second one—a change in student per-

[52] We did not ask again after the intervention, so we cannot look at the effect of rank feedback on these admission beliefs.

[53] For some students we were not able to match the program they listed in the survey to their final application list in the administrative data (e.g., due to an imprecise free-text response), which explains the slightly smaller sample size.

Table 5: Correlation between misconfidence and perceived admission chances

	Offer belief		Offer belief (only Top 10%)		Offer belief (only CPGE)	
	(1)	(2)	(3)	(4)	(5)	(6)
Misconfidence	6.686**	6.970**	9.668*	10.303*	15.057**	13.970**
	(2.963)	(2.967)	(5.748)	(5.742)	(6.555)	(6.398)
Prestige	-7.275***	-4.268***	-9.257***	11.880**	-11.420***	7.846*
	(0.305)	(0.634)	(1.620)	(5.538)	(1.096)	(4.690)
Prestige^2		-1.152***		-4.669***		-4.301***
		(0.221)		(1.166)		(1.030)
Constant	53.320***	53.203***	64.003***	43.695***	56.453***	38.411***
	(1.729)	(1.732)	(6.189)	(8.119)	(7.192)	(8.179)
Real rank	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓
Adj. R2	0.114	0.119	0.056	0.070	0.160	0.179
Observations	8719	8719	1494	1494	939	939
Clusters	1993	1993	691	691	381	381

Notes: This table reports OLS estimates of the association between student misconfidence and their offer beliefs. The dependent variable is the stated belief that a student receives an offer from a program (in percent). The unit of observation is at the student-program level. Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. A student real rank corresponds to her rank at the national level, using the GPA distribution from the administrative data. All regressions control for the prestige of the programs a student is applying to, both linearly and using a quadratic term (in columns (2), (4), and (6)). Columns (1) and (2) include all students and the programs they ranked. In Column (3) and (4), we only consider applications to programs in the top 10% of the prestige distribution and in Column (5) and (6) we only consider applications to CPGEs. The prestige of a program is defined as the z-standardized average *bac* grade of the students enrolled in the program. All regressions control for student real rank and a set of honor fixed effects. Standard errors are clustered at the student level. Significance levels are indicated by $^* < .1, ^{**} < .05, ^{***} < .01$.

ceived chances of success in a program. Adding to recent literature on the impact of inaccurate beliefs about admission probabilities (Agarwal and Somaini, 2018; Kapor et al., 2020; Tincani et al., 2023; Larroucau et al., 2021; Arteaga et al., 2022), our results show that the more confident a student is, the larger they perceive their admission chances at competitive programs. Our intervention, by correcting under- and over-confidence, primarily affected students' applications by changing their perceived admission chances.

8 Conclusion

We show that self-confidence plays a key role in college choice; a very high-stakes environment. We document large differences in applications between male and female students and between high- and low-SES students. While there might be many reasons for these differences, including preferences, information asymmetries, and budget constraints, we investigate the understudied channel of academic self-confidence. We present our results in three building blocks. First, using the survey data we collect, we show large gender and social gaps in confidence, especially for high-ability students; a group of students for whom underconfidence is particularly costly, as they have high admission chances in top programs. Second, we show that misconfidence is strongly associated with the prestige of college applications. Third, based on this observation, we design a simple, cheap, and easily scalable intervention, which consists of providing feedback to students on their relative rank in the national test score distribution. This intervention decreases how much confidence matters for college applications. The intervention also substantially reduces the gender and social gap in the prestige of the college applications and in the likelihood of applying to elite programs (CPGE). These results show that confidence has a clear and large causal effect on students' college applications and on their admissions. Confidence gaps between males and females and between students with a high and low SES are one of the driving forces of the gender and social college application gaps.

Our large treatment effect prompts questions about when similar effects might occur. A key factor is whether a country has a standardized college entrance test, which gives students a clearer sense of their national rank. France lacks such a test, as do many countries like Canada, Germany, Denmark, Austria, Italy (for most subjects), Mexico, the Netherlands, Finland, and others.[54] In these countries, our intervention may yield comparable or even larger effects as students are often unaware of their within-class GPA rank, potentially increasing misperceptions of their national rank.

[54]Information about college admission practices in different countries comes from the excellent survey in Immorlica et al. (2020).

In contrast, in many countries, students know their scores on centralized exams before applying to college, as in Hungary, Chile, China, Brazil, and Australia, making it easier to infer their rank and reducing misconfidence. In these settings, our intervention may have less impact.[55] While centralized exams have drawbacks, they may mitigate girls' underconfidence in sparse-information environments.[56]

While our intervention is easily scalable, its effects may vary due to potential congestion effects—an aspect we aim to explore in future research. Nonetheless, we are confident that an expanded version of this intervention could help narrow gender and socioeconomic gaps, provided that high-achieving female and low-SES students remain more underconfident than their male and high-SES counterparts.

Our results are relevant for policymakers designing school and college admissions. While selecting the right mechanism is crucial, it is not enough; policymakers must also consider the information provided to students to help them make informed choices. Research highlights the value of sharing historical cutoff grades (Immorlica et al., 2020; Hakimov et al., 2023), program quality (Hastings and Weinstein, 2008), and admission chances (Kapor et al., 2020). Our intervention offers an affordable way to address gender and social inequalities among high-achieving students, expanding the tools available for designing equitable admissions systems.

References

Agarwal, Nikhil and Paulo Somaini, "Demand analysis using strategic reports: An application to a school choice mechanism," *Econometrica*, 2018, *86* (2), 391–444.

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow, "The Welfare Effects of Social Media," *American Economic Review*, mar 2020, *110* (3), 629–676.

Almås, Ingvild, Alexander W. Cappelen, Kjell G. Salvanes, Erik Ø. Sørensen, and Bertil Tungodden, "Willingness to Compete: Family Matters," *Management Science*, 2016, *62* (8), 2149–2162.

Altonji, Joseph G, Peter Arcidiacono, and Arnaud Maurel, "The analysis of field choice in college and graduate school: Determinants and wage effects," in "Handbook of the Economics of Education," Vol. 5, Elsevier, 2016, pp. 305–396.

Andrabi, Tahir, Jishnu Das, and Asim Ijaz Khwaja, "Report cards: The impact of providing school and child test scores on educational markets," *American Economic Review*, 2017, *107* (6), 1535–63.

Anelli, Massimo, "The returns to elite university education: A quasi-experimental analysis," *Journal of the European Economic Association*, 2020, *18* (6), 2824–2868.

[55] Although the existence of a centralized exam is likely to be a key factor determining how well our results would replicate in different countries, other features of the college admission process might also play a role, such as the extent to which colleges rely on test scores as admission criteria (versus geographical preferences, legacy, or others), whether colleges use quotas for certain groups of students, whether all colleges use the same admission criteria, and whether these criteria are transparent.

[56] Recent studies show that centralized exams can disadvantage girls, who often underperform under pressure (Cai et al., 2019; Arenas and Calsamiglia, forthcoming).

Angrist, Joshua, David Autor, and Amanda Pallais, "Marginal effects of merit aid for low-income students," *The Quarterly Journal of Economics*, 2022, *137* (2), 1039–1090.

Arcidiacono, Peter and Michael Lovenheim, "Affirmative action and the quality-fit trade-off," *Journal of Economic Literature*, 2016, *54* (1), 3–51.

Arenas, Andreu and Caterina Calsamiglia, "The design of university entrance exams and its implications for gender gaps," *Management Science*, forthcoming.

Arteaga, Felipe, Adam J Kapor, Christopher A Neilson, and Seth D Zimmerman, "Smart Matching Platforms and Heterogeneous Beliefs in Centralized School Choice," *The Quarterly Journal of Economics*, 2022, *137* (3), 1791–1848.

Azmat, Ghazala and Nagore Iriberri, "The importance of relative performance feedback information: Evidence from a natural experiment using high school students," *Journal of Public Economics*, 2010, *94* (7-8), 435–452.

_ , Manuel Bagues, Antonio Cabrales, and Nagore Iriberri, "What you don't know... can't hurt you? A natural field experiment on relative performance feedback in higher education," *Management Science*, 2019, *65* (8), 3714–3736.

Barber, Brad M and Terrance Odean, "Boys will be boys: Gender, overconfidence, and common stock investment," *The Quarterly Journal of Economics*, 2001, *116* (1), 261–292.

Barron, Kai and Christina Gravert, "Confidence and career choices: An experiment," *The Scandinavian Journal of Economics*, 2022, *124* (1), 35–68.

Bergman, Peter, Jeffrey T Denning, and Dayanand Manoli, "Is information enough? The effect of information about education tax benefits on student outcomes," *Journal of Policy Analysis and Management*, 2019, *38* (3), 706–731.

Bettinger, Eric, Oded Gurantz, Laura Kawano, Bruce Sacerdote, and Michael Stevens, "The long-run impacts of financial aid: Evidence from California's Cal Grant," *American Economic Journal: Economic Policy*, 2019, *11* (1), 64–94.

Bettinger, Eric P, Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu, "The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment," *The Quarterly Journal of Economics*, 2012, *127* (3), 1205–1242.

Black, Sandra E, Jeffrey T Denning, and Jesse Rothstein, "Winners and losers? the effect of gaining and losing access to selective colleges on education and labor market outcomes," *American Economic Journal: Applied Economics*, 2023, *15* (1), 26–67.

_ , Kalena E Cortes, and Jane Arnold Lincove, "Academic undermatching of high-achieving minority students: Evidence from race-neutral and holistic admissions policies," *American Economic Review*, 2015, *105* (5), 604–10.

Blau, Francine D and Lawrence M Kahn, "The gender wage gap: Extent, trends, and explanations," *Journal of Economic Literature*, 2017, *55* (3), 789–865.

Bleemer, Zachary, "Affirmative action, mismatch, and economic mobility after California's Proposition 209," *The Quarterly Journal of Economics*, 2022, *137* (1), 115–160.

_ , "Top percent policies and the return to postsecondary selectivity," *Research & Occasional Paper Series: CSHE*, 2024, *1.*

Bó, Inácio and Rustamdjan Hakimov, "The iterative deferred acceptance mechanism," *The Economic Journal*, jul 2019, *130* (626), 356–392.

Bó, Inácio and Rustamdjan Hakimov, "Pick-an-object mechanisms," *Management Science*, 2024, *70* (7), 4693–4721.

Bobba, Matteo and Veronica Frisancho, "Self-perceptions about academic achievement: Evidence from Mexico City," *Journal of Econometrics*, 2022, *231* (1), 58–73.

_ , _ , and Marco Pariguana, "Perceived Ability and School Choices: Experimental Evidence and Scale-up Effects," *Working paper*, July 2024.

Boneva, Teodora, Thomas Buser, Armin Falk, and Fabian Kosse, "The origins of gender differences in competitiveness and earnings expectations: Causal evidence from a mentoring intervention," *HCEO Working Paper*, Oct 2021, *2021-049*.

Bonneau, Cécile and Sébastien Grobon, "Unequal Access to Higher Education Based on Parental Income: Evidence from France," *World Inequality Lab – Working Paper N° 2022/01*, 2022.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, "Beliefs about gender," *American Economic Review*, 2019, *109* (3), 739–73.

Boring, Anne and Jennifer Brown, "Gender, competition and choices in higher education," *Working paper*, 2016.

Bruhin, Adrian, Fidel Petros, and Luís Santos-Pinto, "The role of self-confidence in teamwork: Experimental evidence," *Experimental Economics*, 2024, pp. 1–26.

Burks, Stephen V, Jeffrey P Carpenter, Lorenz Goette, and Aldo Rustichini, "Overconfidence and social signalling," *The Review of Economic Studies*, 2013, *80* (3), 949–983.

Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek, "Gender, Competitiveness, and Career Choices," *The Quarterly Journal of Economics*, 2014, *129* (3), 1409–1447.

_ , _ , and _ , "Can competitiveness predict education and labor market outcomes? Evidence from incentivized choice and survey measures," *Tinbergen Institute Discussion Paper*, Aug 2020, *2020-048/I*.

_ , Noemi Peter, and Stefan C. Wolter, "Willingness to compete, gender and career choices along the whole ability distribution," *Experimental Economics*, 2022.

Cai, Xiqian, Yi Lu, Jessica Pan, and Songfa Zhong, "Gender Gap under Pressure: Evidence from China's National College Entrance Examination," *The Review of Economics and Statistics*, 2019, *101* (2), 249–263.

Campus France, "Tuition Fees in France," https://www.campusfrance.org/en/tuition-fees-France (retrieved 12/04/2022) 2022.

Carlana, Michela, Eliana La Ferrara, and Paolo Pinotti, "Goals and gaps: Educational careers of immigrant children," *Econometrica*, 2022, *90* (1), 1–29.

Chen, Roy, Peter Katuscak, Thomas Kittsteiner, and Katharina Kütter, "Do People Misreport in Strategy-Proof Mechanisms to Avoid Disappointment?," *Available at SSRN 4410915*, 2023.

Chen, Yan and Yinghua He, "Information acquisition and provision in school choice: an experimental study," *Journal of Economic Theory*, 2021, *197*, 105345.

Chetty, Raj, David J Deming, and John N Friedman, "Diversifying society's leaders? The causal effects of admission to highly selective private colleges," *NBER Working Paper 31492*, July 2023.

_ , John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan, "Income segregation and intergenerational mobility across colleges in the United States," *The Quarterly Journal of Economics*, 2020, *135* (3), 1567–1633.

Cortés, Patricia, Jessica Pan, Laura Pilossoph, Ernesto Reuben, and Basit Zafar, "Gender differences in job search and the earnings gap: Evidence from the field and lab," *The Quarterly Journal of Economics*, 2023, *138* (4), 2069–2126.

Cour des Comptes, "Un premier bilan de l'accès à l'enseignement supérieur dans le cadre de la loi orientation et réussite des étudiants, February 2020," https://www.ccomptes.fr/fr/publications/acces-lenseignement-superieur-premier-bilan-de-la-loi-orientation-et-reussite-des (retrieved 01/25/2022) feb 2020.

Dabbaghian, Gabriele and Madeleine Péron, "Tout diplôme mérite salaire? Une estimation des rendements privés de l'enseignement supérieur en France et de leur évolution," *Rapport du Conseil d'Analyse Economique (CAE)*, 2021, *075.*

Dargnies, Marie-Pierre, Rustamdjan Hakimov, and Dorothea Kübler, "Self-confidence and unraveling in matching markets," *Management Science*, 2019, *65* (12), 5603–5618.

_ , _ , and _ , "Aversion to hiring algorithms: Transparency, gender profiling, and self-confidence," *Management Science*, 2024.

Delaney, Judith M and Paul J Devereux, "The economics of gender and educational achievement: Stylized facts and causal evidence," in "Oxford Research Encyclopedia of Economics and Finance," Oxford University Press, 2021.

_ and _ , "High school rank in math and English and the gender gap in STEM," *Labour Economics*, 2021, *69*, 101969.

Denning, Jeffrey T, Richard Murphy, and Felix Weinhardt, "Class rank and long-run outcomes," *The Review of Economics and Statistics*, 2018, pp. 1–45.

Dillon, Eleanor Wiske and Jeffrey Andrew Smith, "The consequences of academic match between students and colleges," *Journal of Human Resources*, 2020, *55* (3), 767–808.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner, "Individual risk attitudes: measurement, determinants, and behavioral consequences," *Journal of the European Economic Association*, 2011, *9* (3), 522–550.

Dreyfuss, Bnaya, Ofer Glicksohn, Ori Heffetz, and Assaf Romm, "Deferred Acceptance with News Utility," Technical Report, National Bureau of Economic Research 2022.

_ , Ori Heffetz, and Matthew Rabin, "Expectations-based loss aversion may help explain seemingly dominated choices in strategy-proof mechanisms," *American Economic Journal: Microeconomics*, 2022, *14* (4), 515–555.

_ , _ , and _ , "Expectations-Based Loss Aversion May Help Explain Seemingly Dominated Choices in Strategy-Proof Mechanisms," *American Economic Journal: Microeconomics*, 2022, *14* (4), 515–555.

Dur, Umut, Scott Duke Kominers, Parag A Pathak, and Tayfun Sönmez, "Reserve design: Unintended consequences and the demise of Boston's walk zones," *Journal of Political Economy*, 2018, *126* (6), 2457–2479.

Dynarski, Susan, "Hope for whom? Financial aid for the middle class and its impact on college attendance," *National Tax Journal*, 2000, *53* (3), 629–661.

_ , CJ Libassi, Katherine Michelmore, and Stephanie Owen, "Closing the gap: The effect of reducing complexity and uncertainty in college pricing on the choices of low-income students," *American Economic Review*, 2021, *111* (6), 1721–56.

Falk, Armin, Fabian Kosse, and Pia Pinger, "Mentoring and Schooling Decisions: Causal Evidence," June 2020. https://docs.iza.org/dp13387.pdf (retrieved 05/25/2022).

Franco, Catalina, "How does Relative Performance Feedback Affect Beliefs and Academic Decisions? Evidence from a Field Experiment," January 2019. http://www-personal.umich.edu/~cfrancob/Franco_JMP.pdf (retrieved 11/19/22).

French Ministry of Education, "Modalités d'organisation de l'examen du baccalauréat général et technologique de la session 2021, pour l'année scolaire 2020-2021, dans le contexte de l'épidémie de Covid-19," *Bulletin officiel de l'éducation nationale, de la jeunesse et des sports, Note de service du 9-6-2021*, 2021, p. https://www.education.gouv.fr/bo/21/Hebdo23/MENE2117192N.htm.

Garbiras-Díaz, Natalia and Mateo Montenegro, "All Eyes on Them: A Field Experiment on Citizen Oversight and Electoral Integrity," *American Economic Review*, 2022, *112* (8), 2631–2668.

Gonczarowski, Yannai A, Ori Heffetz, and Clayton Thomas, "Strategyproofness-exposing mechanism descriptions," *arXiv preprint arXiv:2209.13148*, 2022.

Goodman, Joshua, Michael Hurwitz, and Jonathan Smith, "Access to 4-Year Public Colleges and Degree Completion," *Journal of Labor Economics*, 2017, *35* (3), 829–867.

Goodman, Sarena, "Learning from the test: Raising selective college enrollment by providing information," *The Review of Economics and Statistics*, 2016, *98* (4), 671–684.

Goulas, Sofoklis and Rigissa Megalokonomou, "Knowing who you actually are: The effect of feedback on short-and longer-term outcomes," *Journal of Economic Behavior & Organization*, 2021, *183*, 589–615.

Grenet, Julien, YingHua He, and Dorothea Kübler, "Preference discovery in university admissions: The case for dynamic multioffer mechanisms," *Journal of Political Economy*, 2022, *130* (6), 1427–1476.

Guyon, Nina and Elise Huillery, "Biased Aspirations and Social Inequality at School: Evidence from French Teenagers," *The Economic Journal*, jun 2020, *131* (634), 745–796.

Hakimov, Rustamdjan, Dorothea Kübler, and Siqi Pan, "Costly information acquisition in centralized matching markets," *Quantitative Economics*, 2023, *14* (4), 1447–1490.

Hastings, Justine S and Jeffrey M Weinstein, "Information, school choice, and academic achievement: Evidence from two experiments," *The Quarterly Journal of Economics*, 2008, *123* (4), 1373–1414.

_ , Christopher A Neilson, and Seth D Zimmerman, "Are some degrees worth more than others? Evidence from college admission cutoffs in Chile," *National Bureau of Economic Research*, 2013.

Hoekstra, Mark, "The effect of attending the flagship state university on earnings: A discontinuity-based approach," *The review of economics and statistics*, 2009, *91* (4), 717–724.

Hoxby, Caroline and Sarah Turner, "Expanding College Opportunities for High-Achieving, Low Income Students," 2013. https://www8.gsb.columbia.edu/programs/sites/programs/files/finance/Applied%20Microeconomics/Caroline%20Hoxby.pdf (retrieved 01/19/2022).

Hoxby, Caroline M and Christopher Avery, "The missing "one-offs": The hidden supply of high-achieving, low income students," Technical Report, National Bureau of Economic Research 2012.

_ and Sarah Turner, "What high-achieving low-income students know about college," *American Economic Review*, 2015, *105* (5), 514–17.

Huffman, David, Collin Raymond, and Julia Shvets, "Persistent overconfidence and biased memory: Evidence from managers," *American Economic Review*, 2022, *112* (10), 3141–3175.

Hvidberg, Kristoffer B, Claus T Kreiner, and Stefanie Stantcheva, "Social positions and fairness views on inequality," *Review of Economic Studies*, 2023, *90* (6), 3083–3118.

Immorlica, Nicole, Jacob Leshno, Irene Lo, and Brendan Lucier, "Information acquisition in matching markets: The role of price discovery," *Available at SSRN 3705049*, 2020.

Insee, "Classification of professions and socioprofessional categories," https://www.insee.fr/en/metadonnees/definition/c1493 (retrieved 03/08/2022) oct 2016.

_ , "Salaires dans le secteur privé," https://www.insee.fr/fr/statistiques/4478921 (retrieved 03/08/2022) apr 2020.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer, "Worker beliefs about outside options," *The Quarterly Journal of Economics*, 2024, p. 1505–1556.

Jensen, Robert, "The (perceived) returns to education and the demand for schooling," *The Quarterly Journal of Economics*, 2010, *125* (2), 515–548.

Jäger, Kai, "The potential of online sampling for studying political activists around the world and across time," *Political Analysis*, 11 2022, *25*, 329–343.

Kapor, Adam J., Christopher A. Neilson, and Seth D. Zimmerman, "Heterogeneous Beliefs and School Choice Mechanisms," *American Economic Review*, 2020, *110* (5), 1274–1315.

Kirkeboen, Lars J, Edwin Leuven, and Magne Mogstad, "Field of study, earnings, and self-selection," *The Quarterly Journal of Economics*, 2016, *131* (3), 1057–1111.

Landaud, Fanny and Éric Maurin, "Aim High and Persevere! Competitive Pressure and Access Gaps in Top Science Graduate Programs," *Working Paper*, 2021.

_ , Son Thierry Ly, and Éric Maurin, "Competitive Schools and the Gender Gap in the Choice of Field of Study," *Journal of Human Resources*, 2019, *55* (1), 278–308.

Larroucau, Tomás, Manuel Martínez, Christopher Neilson, and Ignacio Rios, "Application Mistakes and Information frictions in College Admissions," November 2021. https://tlarroucau.github.io/Mistakes_College.pdf (retrieved 24/02/2022).

Leroux, Marie, "Sondage : Instagram, réseau social préféré des jeunes en 2020," https://diplomeo.com/actualite-sondage_reseaux_sociaux_jeunes_2020 (retrieved 01/20/2022) 2020.

Li, Shengwu, "Obviously strategy-proof mechanisms," *American Economic Review*, 2017, *107* (11), 3257–3287.

L'étudiant, "Comment sera noté le bac 2021 ?," *https://www.letudiant.fr/bac/comment-sera-note-le-bac-2021.html*, 2021.

MacLeod, W. Bentley, Evan Riehl, Juan E. Saavedra, and Miguel Urquiola, "The Big Sort: College Reputation and Labor Market Outcomes," *American Economic Journal: Applied Economics*, 2017, *9* (3), 223–261.

Malmendier, Ulrike and Geoffrey Tate, "CEO overconfidence and corporate investment," *The journal of finance*, 2005, *60* (6), 2661–2700.

Meisner, Vincent, "Report-dependent utility and strategy-proofness," *Management Science*, 2023, *69* (5), 2733–2745.

_ , "Report-dependent utility and strategy-proofness," *Management Science*, 2023, *69* (5), 2733–2745.

_ **and Jonas von Wangenheim**, "Loss aversion in strategy-proof school-choice mechanisms," *Journal of Economic Theory*, 2023, *207*, 105588.

_ **and Jonas von Wangenheim**, "Loss aversion in strategy-proof school-choice mechanisms," *Journal of Economic Theory*, 2023, *207*, 105588.

Möbius, Markus M, Muriel Niederle, Paul Niehaus, and Tanya S Rosenblat, "Managing self-confidence: Theory and experimental evidence," *Management Science*, 2022, *68* (11), 7793–8514.

Moore, Don A and Paul J Healy, "The trouble with overconfidence.," *Psychological review*, 2008, *115* (2), 502.

Murphy, Richard and Felix Weinhardt, "Top of the class: The importance of ordinal rank," *The Review of Economic Studies*, 2020, *87* (6), 2777–2826.

Niederle, Muriel and Lise Vesterlund, "Do women shy away from competition? Do men compete too much?," *The Quarterly Journal of Economics*, 2007, *122* (3), 1067–1101.

Ortoleva, Pietro and Erik Snowberg, "Overconfidence in political behavior," *American Economic Review*, 2015, *105* (2), 504–35.

Oster, Emily, Ira Shoulson, and E Ray Dorsey, "Optimal expectations and limited medical testing: Evidence from Huntington disease," *American Economic Review*, 2013, *103* (2), 804–830.

Otero, Sebastián, Nano Barahona, and Cauê Dobbin, "Affirmative Action in Centralized College Admission Systems: Evidence from Brazil," *Working Paper*, 2021.

Page, Lindsay C and Judith Scott-Clayton, "Improving college access in the United States: Barriers and policy responses," *Economics of Education Review*, 2016, *51*, 4–22.

Pan, Siqi, "The instability of matching with overconfident agents," *Games and Economic Behavior*, 2019, *113*, 396–415.

Patnaik, Arpita, Matthew Wiswall, and Basit Zafar, "College Majors," in Brian P. McCall, ed., *The Routledge Handbook of the Economics of Education*, Oxon, UK; New York, NY: Routledge, 2021.

Pycia, Marek and Peter Troyan, "A theory of simplicity in games and mechanism design," *Econometrica*, 2023, *91* (4), 1495–1526.

Rees-Jones, Alex and Ran Shorrer, "Behavioral Economics in Education Market Design: A Forward-Looking Review," *Journal of Political Economy Microeconomics*, 2023, *1* (3).

_ , _ , and Chloe J Tergiman, "Correlation Neglect in Student-to-School Matching," *American Economic Journal: Microeconomics*, forthcoming.

Reuben, Ernesto, Matthew Wiswall, and Basit Zafar, "Preferences and Biases in Educational Choices and Labour Market Expectations: Shrinking the Black Box of Gender," *The Economic Journal*, jan 2017, *127* (604), 2153–2186.

_ , Paola Sapienza, and Luigi Zingales, "Taste for competition and the gender gap among young business professionals," nov 2019. http://www.ereuben.net/research/GenderGapCompetitiveness.pdf (retrieved 11/10/2022).

Rosenzweig, L. R., P. Bergquist, K. Hoffmann Pham, F. Rampazzo, and M. Mildenberger, "Survey sampling in the Global South using Facebook advertisements," 2020. https://doi.org/10.31235/osf.io/dka8f (retrieved 07/26/2023).

Samuels, David and Cesar Zucco, "Using Facebook as a Subject Recruitment Tool for Survey-Experimental Research," 2013. Available at SSRN 2101458.

Santos-Pinto, Luis and Leonidas Enrique de la Rosa, "Overconfidence in labor markets," *Handbook of Labor, Human Resources and Population Economics*, 2020, pp. 1–42.

Saygin, Perihan Ozge, "Gender differences in preferences for taking risk in college applications," *Economics of Education Review*, 2016, *52*, 120–133.

Schneider, Daniel and Kristen Harknett, "What's to Like? Facebook as a Tool for Survey Data Collection," *Sociological Methods & Research*, 2022, *51* (1), 108–140.

Scott-Clayton, Judith and Lauren Schudde, "The consequences of performance standards in need-based aid evidence from community colleges," *Journal of Human Resources*, 2020, *55* (4), 1105–1136.

SIES, "BPBAC : Inscriptions dans les formations post-baccalauréat des établissements du second degré," 2021. https://doi.org/10.34724/CASD.458.4858.V1.

_ , "SISE Inscrits UNIV : SISE Inscrits Université," 2021. https://doi.org/10.34724/CASD.483.4576.V1.

_ , "BPBAC : Inscriptions dans les formations post-baccalauréat des établissements du second degré," 2022. https://doi.org/10.34724/CASD.458.5279.V1.

_ , "Psup'stat : Bases statistiques issues de l'application Parcoursup - 2021," 2022. http://doi.org/10.34724/CASD.469.4130.V2.

_ , "SISE Inscrits UNIV : SISE Inscrits Université," 2022. https://doi.org/10.34724/CASD.483.5082.V1.

_ , "Parcoursup brut : Remontées de l'application Parcoursup - 2021," 2023. http://doi.org/10.34724/CASD.526.4495.V1.

Sterling, Adina D, Marissa E Thompson, Shiya Wang, Abisola Kusimo, Shannon Gilmartin, and Sheri Sheppard, "The confidence gap predicts the gender pay gap among STEM graduates," *Proceedings of the National Academy of Sciences*, 2020, *117* (48), 30303–30308.

Terrier, Camille, Daniel L Chen, and Matthias Sutter, "COVID-19 within families amplifies the prosociality gap between adolescents of high and low socioeconomic status," *Proceedings of the National Academy of Sciences*, 2021, *118* (46), e2110891118.

Tincani, Michela M., Fabian Kosse, and Enrico Miglino, "College Access When Preparedness Matters: New Evidence from Large Advantages in College Admissions," *Working Paper*, October 2023.

Wiswall, Matthew and Basit Zafar, "How Do College Students Respond to Public Information about Earnings?," *Journal of Human Capital*, jun 2015, *9* (2), 117–169.

_ **and** _ , "Preference for the Workplace, Investment in Human Capital, and Gender," *The Quarterly Journal of Economics*, 2018, *133* (1), 457–507.

Zhang, Baobao, Matto Mildenberger, Peter D. Howe, Jennifer Marlon, Seth A. Rosenthal, and Anthony Leiserowitz, "Quota sampling using Facebook advertisements," *Political Science Research and Methods*, 2020, *8* (3), 558–564.

Zimmerman, Seth D, "Elite colleges and upward mobility to top jobs and top incomes," *American Economic Review*, 2019, *109* (1), 1–47.

Appendix

A Additional Tables and Figures

Table A.1: Descriptive statistics

		Survey data			
	Admin data	Full Sample	Control group	Treated group	Difference (p-value)
	(1)	(2)	(3)	(4)	(5)
Female	0.558	0.620	0.624	0.616	(0.722)
Age	17.539	17.523	17.520	17.527	(0.791)
Low SES	0.259	0.306	0.308	0.305	(0.876)
Risk preference		7.633	7.655	7.609	(0.624)
GPA	13.468	13.715	13.725	13.705	(0.822)
Honors (Bac grade)					
No honors	0.258	0.233	0.234	0.231	(0.873)
Honors	0.336	0.339	0.326	0.354	(0.184)
High honors	0.263	0.271	0.269	0.274	(0.831)
Highest honors	0.144	0.157	0.171	0.142	(0.071)
Region (*Académie*)					
Ile-de-France	0.195	0.209	0.197	0.222	(0.164)
Share disadvantaged	0.378	0.377	0.377	0.378	(0.721)
Survey pre-treatment					
Number of programs listed		4.961	4.962	4.959	(0.983)
Avg. offer probability		0.602	0.599	0.605	(0.507)
Guessed rank		0.518	0.512	0.524	(0.130)
Misconfidence		0.059	0.050	0.069	(0.083)
No honors		0.270	0.254	0.287	(0.080)
Honors		0.114	0.110	0.119	(0.561)
High honors		-0.056	-0.053	-0.059	(0.692)
Highest honors		-0.174	-0.181	-0.165	(0.413)
Overconfidence		0.126	0.121	0.132	(0.118)
Underconfidence		0.067	0.071	0.064	(0.179)
Number of observations	420,745	2,034	1,047	987	

Notes: This table reports descriptive statistics for the administrative data (column 1) and the survey data, decomposed into the full sample (column 2), the control group (column 3), and the treated group (column 4). Column 5 shows the p-value of a t-test comparing the mean values in the treatment and control group. Statistics for the administrative data pertain to *bac général* students who graduated in 2021. "Region" refers to educational districts (*académie*) in which a student went to high school. "Share disadvantaged" corresponds to the share of students who receive a state scholarship in that district. Finally, the table reports mean values of variables that we collected in the survey, pre-treatment: the number of programs respondents listed when asked for their applications list, the mean belief about receiving an offer from these programs, the average guessed rank, misconfidence (defined as guessed rank minus real rank), misconfidence by honors, overconfidence (guessed rank minus real rank, for overconfident students only), and underconfidence (real rank minus guessed rank, for underconfident students only).

Table A.2: Descriptive statistics on college applications
Comparison between administrative and survey data

	Admin data	Survey data (Control group)
Panel A: Application list		
Max(prestige)	2.390	2.290
	(1.106)	(1.129)
Min(prestige)	-0.625	-0.519
	(0.570)	(0.527)
Mean(prestige)	0.893	0.873
	(0.908)	(0.886)
One elite program (CPGE)	0.266	0.271
	(0.442)	(0.445)
Number of applications	11.244	10.830
	(6.3311)	(5.865)
Number of observations	405,771	1,047
Panel B: Accepted program		
Prestige	0.607	0.719
	(1.183)	(1.176)
Elite program (CPGE)	0.103	0.091
	(0.304)	(0.287)
Number of observations	353,277	914

Notes: This table reports means and standard deviations (in parentheses) of variables pertaining to student application list (Panel A) and accepted program (Panel B). Descriptive statistics for the survey sample (column 2) are restricted to the control group because application lists and accepted programs are determined post treatment. Max(prestige), Min(prestige), and Mean(prestige) refer to the maximal, minimum, and mean prestige of the application list, respectively. Prestige is defined at the program level as the z-transformed average grade of the admitted students.

Table A.3: Confidence gaps by gender and SES
(Misconfidence defined using GPA distribution from the pre-survey sample)

	Misconfidence (1)	Underconfidence (2)	Overconfidence (3)
	Panel A: Gender Gap		
All students	-0.018**	0.028***	0.015*
	(0.007)	(0.010)	(0.008)
	[2034]	[852]	[1138]
Students with ...			
... no honors	0.037**	0.008	0.043**
	(0.016)	(0.030)	(0.017)
	[473]	[28]	[438]
... honors	-0.020*	0.002	-0.006
	(0.011)	(0.013)	(0.011)
	[690]	[193]	[491]
... high honors	-0.036***	0.020	0.013
	(0.012)	(0.014)	(0.010)
	[552]	[337]	[189]
... highest honors	-0.083***	0.066***	-0.019
	(0.019)	(0.020)	(0.027)
	[319]	[294]	[20]
	Panel B: Social Gap		
All students	-0.020**	0.035***	0.006
	(0.008)	(0.010)	(0.009)
	[2000]	[840]	[1116]
Students with ...			
... no honors	0.008	0.012	0.010
	(0.017)	(0.031)	(0.017)
	[462]	[28]	[427]
... honors	-0.026**	0.019	0.001
	(0.013)	(0.014)	(0.013)
	[680]	[190]	[484]
... high honors	-0.028**	0.030*	0.002
	(0.014)	(0.016)	(0.012)
	[544]	[333]	[185]
... highest honors	-0.047**	0.060**	0.039
	(0.024)	(0.023)	(0.031)
	[314]	[289]	[20]
Real rank (pre-survey)	✓	✓	✓

Notes: This table reports the coefficients from separate regressions of misconfidence (column 1), underconfidence (column 2), and overconfidence (column 3) on a binary variable for female students (Panel A) and a binary variable for low-SES students (Panel B). Misconfidence corresponds to the difference between a student guessed ability rank and their real rank. This variable ranges between -1 to 1. Underconfidence is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). Overconfidence is equal to the difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). All regressions control for a student real rank. Confidence measures are defined using the GPA distribution obtained from the pre-survey. After running regressions on the full sample (top coefficient in each panel), we divide the sample by four honors categories which are mutually exclusive. We report robust standard errors in round parentheses and the number of observations in square brackets. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

Table A.4: Confidence gaps by gender and SES
(Misconfidence defined using within-school GPA distribution)

	Misconfidence (1)	Underconfidence (2)	Overconfidence (3)
	Panel A: Gender gap		
All students	-0.019**	0.033***	0.020*
	(0.008)	(0.009)	(0.011)
	[1829]	[1057]	[768]
Students with ...			
... no honors	0.034*	-0.006	0.042**
	(0.019)	(0.026)	(0.019)
	[407]	[60]	[347]
... honors	-0.018	0.017	0.013
	(0.012)	(0.013)	(0.014)
	[628]	[316]	[311]
... high honors	-0.045***	0.030**	-0.027
	(0.013)	(0.013)	(0.020)
	[499]	[407]	[89]
... highest honors	-0.091***	0.087***	-0.001
	(0.020)	(0.020)	(0.023)
	[295]	[274]	[21]
	Panel B: Social gap		
All students	-0.032***	0.035***	-0.003
	(0.009)	(0.009)	(0.011)
	[1797]	[1039]	[754]
Students with ...			
... no honors	-0.012	-0.012	-0.006
	(0.019)	(0.027)	(0.019)
	[396]	[59]	[337]
... honors	-0.034**	0.038***	0.004
	(0.013)	(0.013)	(0.015)
	[619]	[311]	[307]
... high honors	-0.029*	0.031**	-0.004
	(0.015)	(0.015)	(0.020)
	[491]	[399]	[89]
... highest honors	-0.042*	0.041*	0.037
	(0.025)	(0.025)	(0.034)
	[291]	[270]	[21]
Real rank (within-school)	✓	✓	✓

Notes: This table reports the coefficients from separate regressions of misconfidence (column 1), underconfidence (column 2), and overconfidence (column 3) on a binary variable for female students (Panel A) and a binary variable for low-SES students (Panel B). Misconfidence corresponds to the difference between a student guessed ability rank and their real rank. The real rank is calculated using a student within-schools GPA distribution. This variable ranges between -1 to 1. Underconfidence is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). Overconfidence is equal to the difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). All regressions control for a student real rank. Confidence measures are defined using the GPA distribution obtained from the pre-survey. After running regressions on the full sample (top coefficient in each panel), we divide the sample by four honors categories which are mutually exclusive. We report robust standard errors in round parentheses and the number of observations in square brackets. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

Table A.5: Association between misconfidence and offer probability

	All applications		Applications to elite programs (CPGE)	
	(1)	(2)	(3)	(4)
Panel A: Effect of misconfidence				
Misconfidence	-0.017	0.018	-0.022	0.028
	(0.041)	(0.040)	(0.083)	(0.083)
Program prestige		-0.100***		-0.150***
		(0.005)		(0.015)
Panel B: Effect of under- and overconfidence				
Underconfidence	0.057	0.005	0.090	0.000
	(0.077)	(0.068)	(0.122)	(0.122)
Overconfidence	0.018	0.037	0.187	0.116
	(0.049)	(0.050)	(0.116)	(0.107)
Program prestige		-0.100***		-0.149***
		(0.005)		(0.015)
Real rank (pre-survey)	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓
Observations	17229	17199	2017	2017
Mean outcome	0.173	0.173	0.166	0.166

Notes: This table reports the association between student misconfidence and their probability of receiving an offer from a program. In Column (1) and (2), the dependent variable is the probability of receiving an offer (on the first day) from a program a student applied to. In Columns (3) and (4), the dependent variable is the probability of receiving an offer (on the first day) from an elite program (CPGE). Misconfidence corresponds to the difference between a student guessed ability rank and their real rank. This variable ranges between -1 to 1. A student's real rank corresponds to her rank at the national level, using the GPA distribution from the pre-survey. Underconfidence is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). Overconfidence is equal to the difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). The sample includes students from the control group. Standard errors clustered on the student level are reported in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

Table A.6: Association between misconfidence and college applications and admissions
(Misconfidence defined using GPA distribution from the pre-survey sample)

	College Applications				College Admissions	
	Max Prestige (1)	Min Prestige (2)	Mean Prestige (3)	One CPGE (4)	Prestige (5)	CPGE (6)
Panel A.1: Effect of misconfidence (Control group)						
Misconfidence	0.713***	0.111	0.479***	0.326***	0.430**	0.157***
	(0.201)	(0.093)	(0.139)	(0.076)	(0.186)	(0.055)
Panel A.2: Effect of under- and overconfidence (Control group)						
Underconfidence	-0.518*	-0.265	-0.525**	-0.524***	-0.443	-0.275***
	(0.304)	(0.177)	(0.265)	(0.146)	(0.347)	(0.098)
Overconfidence	0.858***	0.011	0.448***	0.181**	0.419**	0.057
	(0.283)	(0.110)	(0.160)	(0.080)	(0.210)	(0.048)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.204	0.124	0.325	0.197	0.457	0.092
Observations	1047	1047	1047	1047	914	914
Mean outcome	2.290	-0.520	0.873	0.271	0.719	0.091
Panel B.1: Effect of misconfidence (Treatment group)						
Misconfidence	0.017	0.062	0.105	0.110	0.320	0.029
	(0.196)	(0.097)	(0.140)	(0.074)	(0.198)	(0.066)
Panel B.2: Effect of under- and overconfidence (Treatment group)						
Underconfidence	-0.288	-0.128	-0.214	-0.108	-0.523	-0.023
	(0.256)	(0.168)	(0.247)	(0.159)	(0.381)	(0.154)
Overconfidence	-0.155	0.021	0.035	0.112	0.170	0.033
	(0.287)	(0.113)	(0.168)	(0.072)	(0.223)	(0.040)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.249	0.115	0.345	0.198	0.470	0.110
Observations	987	987	987	987	879	879
Mean outcome	2.295	-0.522	0.874	0.248	0.663	0.105

Notes: This table reports the association between student misconfidence and their college applications and admissions. Misconfidence is the difference between the guessed rank and the real rank. This variable ranges between -1 to 1. A student's real rank corresponds to their rank in the GPA distribution from the pre-survey sample. Underconfidence is equal to the difference between the real rank and the guessed rank for underconfident students and is zero for overconfident students (hence, scaled between 0 and 1). The larger this variable, the more underconfident a student is. Overconfidence is equal to the difference between the guessed rank and the real rank for overconfident students and zero otherwise (hence, scaled between 0 and 1). The larger this variable, the more overconfident a student is. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE). The sample includes students from the control group. Robust standard errors are reported in parentheses. Significance levels are indicated by * < .1,** < .05,*** < .01.

Table A.7: Effect of rank feedback on college applications and admissions (Separate effects for underconfident and overconfident students)

	College Applications				College Admissions		Dropout
	Max Prestige	Min Prestige	Mean Prestige	One CPGE	Prestige	CPGE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Underconfidence	-0.461	-0.245	-0.484*	-0.478***	-0.445	-0.276***	0.017
	(0.287)	(0.169)	(0.249)	(0.137)	(0.328)	(0.088)	(0.132)
Rank feedback							
× Underconfidence	0.104	0.115	0.227	0.321*	-0.070	0.254*	0.028
	(0.363)	(0.211)	(0.319)	(0.190)	(0.458)	(0.153)	(0.181)
Overconfidence	0.711***	-0.001	0.377**	0.128*	0.400**	0.046	0.043
	(0.252)	(0.100)	(0.148)	(0.075)	(0.197)	(0.045)	(0.135)
Rank feedback							
× Overconfidence	-0.723**	0.039	-0.270	0.036	-0.211	-0.002	0.000
	(0.300)	(0.124)	(0.186)	(0.093)	(0.253)	(0.066)	(0.159)
Rank feedback	0.107	-0.007	0.041	-0.042	0.027	0.002	-0.010
	(0.068)	(0.036)	(0.051)	(0.028)	(0.068)	(0.022)	(0.034)
Constant	1.378***	-0.785***	0.092*	-0.019	-0.532***	-0.040**	0.431***
	(0.091)	(0.040)	(0.056)	(0.027)	(0.070)	(0.017)	(0.049)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Observations	2034	2034	2034	2034	1793	1793	1696

Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the role played by confidence in student college choices. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability distribution. Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE); in Column (7) an indicator of whether a student did not re-enroll in the same program after the first year. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

Table A.8: Effect of rank feedback on college applications and admissions
(Using national GPA distribution to define misconfidence)

	College Applications				College Admissions		Dropout
	Max Prestige	Min Prestige	Mean Prestige	One CPGE	Prestige	CPGE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Misconfidence	0.601***	0.112	0.442***	0.270***	0.472***	0.149***	0.008
	(0.170)	(0.080)	(0.120)	(0.066)	(0.161)	(0.046)	(0.088)
Rank feedback	-0.004	0.014	0.014	-0.015	-0.006	0.017	-0.002
	(0.045)	(0.022)	(0.033)	(0.018)	(0.040)	(0.013)	(0.023)
Rank feedback							
× Misconfidence	-0.533***	-0.025	-0.289**	-0.092	-0.122	-0.104**	0.032
	(0.188)	(0.084)	(0.130)	(0.071)	(0.173)	(0.052)	(0.098)
Constant	1.410***	-0.843***	0.049	-0.073***	-0.622***	-0.069***	0.426***
	(0.078)	(0.036)	(0.052)	(0.026)	(0.065)	(0.018)	(0.043)
Real rank	✓	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Adj. R2	0.220	0.127	0.332	0.194	0.460	0.102	0.028
Observations	1910	1910	1910	1910	1793	1793	1607
Mean outcome	2.306	-0.530	0.875	0.262	0.691	0.098	0.301

Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the role played by confidence in student college choices. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability distribution. Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. We define the misconfidence and real rank variables using the GPA distribution from the administrative data. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE); in Column (7) an indicator of whether a student did not re-enroll in the same program after the first year. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

Table A.9: Effect of rank feedback on gender and social gaps in college applications and admissions among non high-achieving students

	College Applications				College Admissions		Dropout
	Max Prestige (1)	Min Prestige (2)	Mean Prestige (3)	One CPGE (4)	Prestige (5)	CPGE (6)	(7)
Panel A: By gender							
Female	-0.266***	0.014	-0.159***	-0.140***	-0.124**	-0.059***	0.044
	(0.071)	(0.032)	(0.049)	(0.027)	(0.060)	(0.018)	(0.035)
Rank feedback	-0.111	-0.017	-0.049	-0.033	-0.070	0.040	0.026
	(0.077)	(0.037)	(0.055)	(0.032)	(0.068)	(0.025)	(0.039)
Rank feedback							
× Female	0.169*	0.041	0.098	0.027	0.082	-0.045	-0.038
	(0.100)	(0.047)	(0.070)	(0.038)	(0.087)	(0.028)	(0.050)
Constant	1.708***	-0.773***	0.298***	0.113***	-0.322***	0.011	0.377***
	(0.065)	(0.030)	(0.043)	(0.025)	(0.054)	(0.016)	(0.035)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Adj. R2	0.133	0.056	0.178	0.104	0.269	0.070	0.012
Observations	1732	1732	1732	1732	1510	1510	1415
Mean outcome	2.132	-0.580	0.705	0.193	0.407	0.064	0.325
Panel B: By SES							
Low-SES	-0.270***	-0.061*	-0.153***	-0.025	-0.105*	-0.018	0.005
	(0.079)	(0.033)	(0.051)	(0.027)	(0.062)	(0.016)	(0.038)
Rank feedback	-0.028	0.002	0.011	-0.004	-0.008	0.018	-0.019
	(0.059)	(0.029)	(0.043)	(0.023)	(0.052)	(0.016)	(0.030)
Rank feedback							
× Low-SES	0.041	0.030	-0.001	-0.039	-0.048	-0.016	0.065
	(0.109)	(0.048)	(0.072)	(0.037)	(0.089)	(0.024)	(0.054)
Constant	1.665***	-0.739***	0.268***	0.043**	-0.352***	-0.016	0.397***
	(0.059)	(0.027)	(0.039)	(0.020)	(0.048)	(0.012)	(0.032)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓	✓
Adj. R2	0.137	0.056	0.182	0.083	0.274	0.045	0.014
Observations	1703	1703	1703	1703	1483	1483	1389
Mean outcome	2.133	-0.578	0.706	0.193	0.408	0.064	0.323

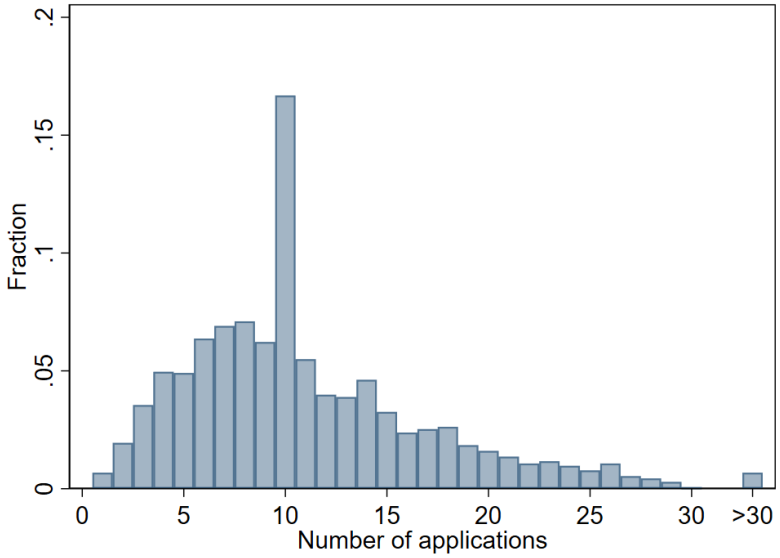
Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the gender gap (panel A) and social gap (panel B) in college applications. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who receive information on their real rank in the ability distribution. Low-SES and Female are dummy variables indicating whether a student is from a low socio-economic background and female, respectively. We run these regressions on the sample of students who did not receive the highest honors. The dependent variables are: In Column (1), the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list; in Column (2), the minimum prestige of the application list; in Column (3) the average prestige of the application list; in Column (4) an indicator of whether a student applies to at least one elite program (CPGE); in Column (5) the prestige of program a student enrolls in; in Column (6) an indicator of whether a student enrolls in an elite program (CPGE); in Column (7) an indicator of whether a student did not re-enroll in the same program after the first year. Only students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by * < .1,** < .05,*** < .01.

Table A.10: Effect of confidence and feedback treatment on acceptance conditional on offer

	Acceptance given offer	
	CPGE	Top 10%
	(1)	(2)
Misconfidence	0.074	0.162
	(0.228)	(0.308)
Sample	Control	Control
Real rank (pre-survey)	✓	✓
Honors FE	✓	✓
Risk preference	✓	✓
Adj. R2	0.017	0.005
Observations	192	121

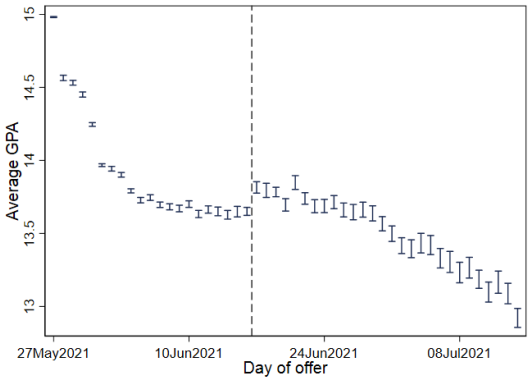
Notes: Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. We define the misconfidence and real rank variables using the GPA distribution from the sample of students in the pre-survey. The dependent variable is an indicator for accepting a prestigious offer conditional on receiving an offer. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

Figure A.1: Number of applications

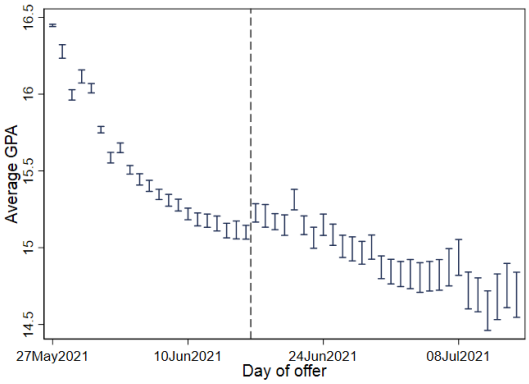


Notes: This figure shows a histogram of the number of applications that students from the general high school track submitted in 2021 (using the administrative data).

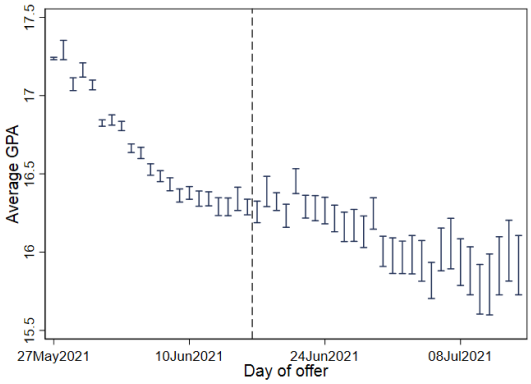
Figure A.2: Average GPA by day of offer



(a) All programs



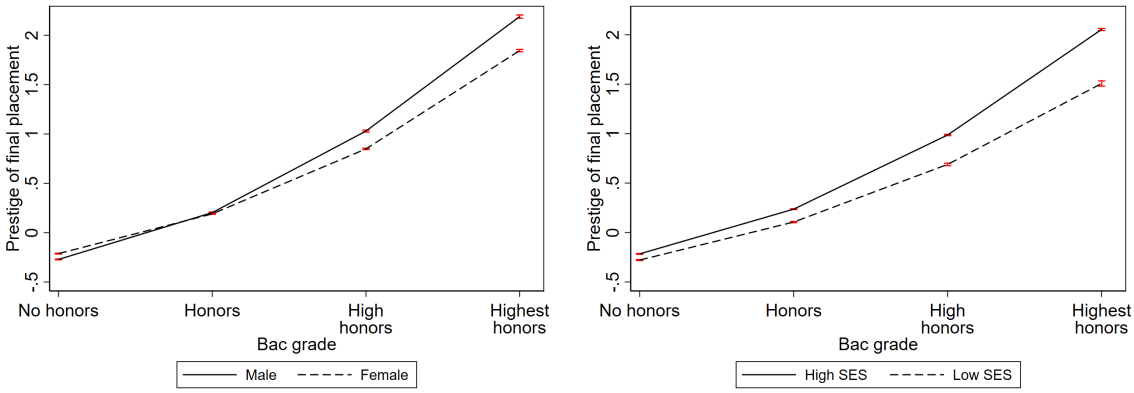
(b) Only elite programs (CPGE)



(c) Only top 10% prestige programs

Notes: This figure reports, day by day, the average GPA of the students who receive offers. We plot the GPA of the first trimester of the second year, which is the GPA we elicit in the survey. The dashed line indicates the start of the complimentary phase, when students can apply to programs with remaining seats. Panel (a) includes offers sent by all programs. Panel (b) only includes offers from the elite tracks (CPGEs). Panel (c) only includes offers from programs in the top 10% of the prestige distribution. We define the prestige of the program as the average high school diploma grades of the students enrolled in the program.

Figure A.3: Gender and social gaps in prestige of accepted program by honors

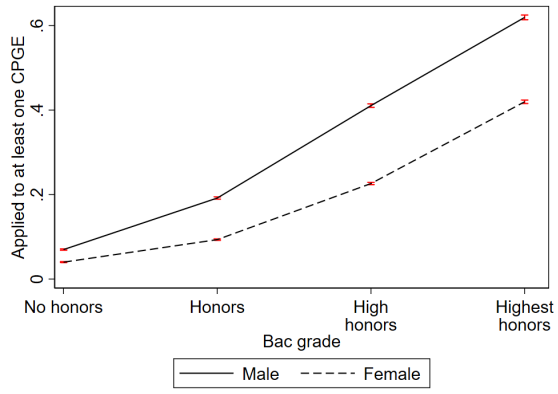


(a) Prestige by gender

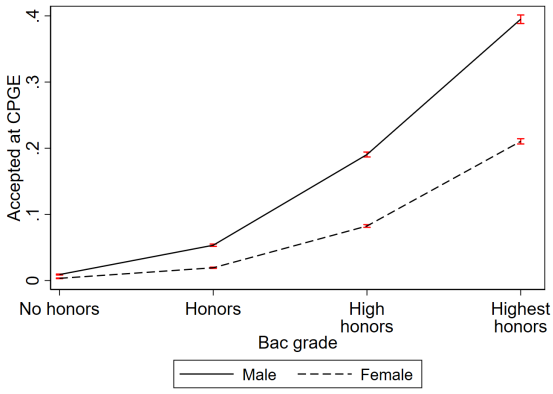
(b) Prestige by SES

Notes: These figures report the prestige of the final match (accepted program) by honor and gender/SES. The prestige of a program is defined as the mean GPA of all enrolled students. Bars indicate 95% confidence intervals.

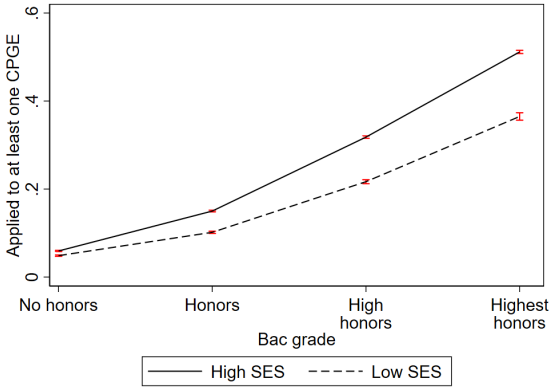
Figure A.4: Gender and social gaps in applications and admission to elite programs (CPGE)



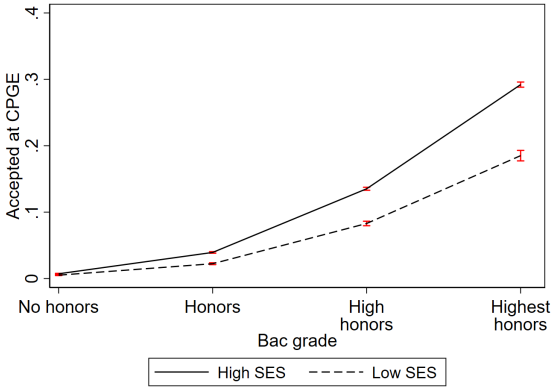
(a) Applied to elite program by gender



(b) Matched to elite program by gender



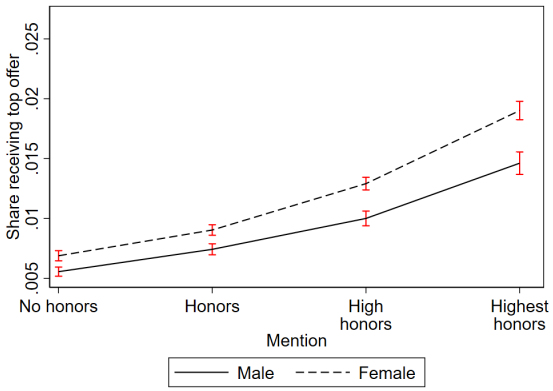
(c) Applied to elite program by SES



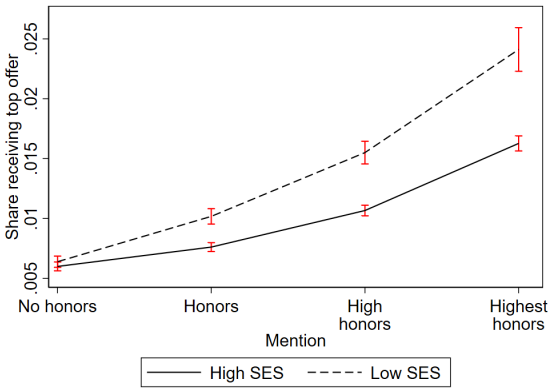
(d) Matched to elite program by SES

Notes: These figures report the probability of applying to at least one elite CPGE program (left panel) and the probability of being matched to an elite program (right panel) by honors and gender (or SES). The 95% confidence intervals are based on predicted values from a regression of applications (resp. matches) on the interaction of honors and female/low SES.

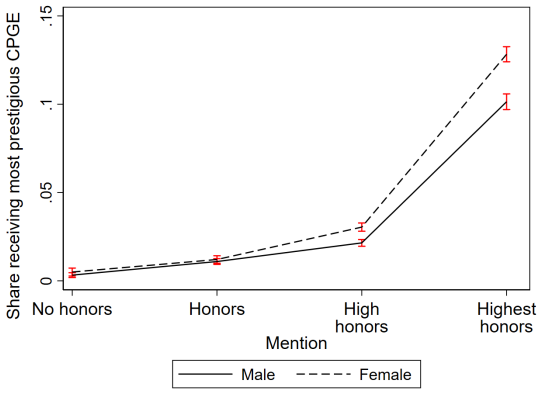
Figure A.5: Gender and social gaps in probability of receiving an offer from the top program



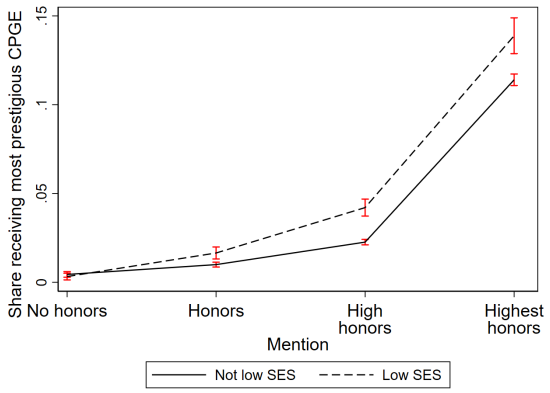
(a) All applications (by gender)



(b) All applications (by SES)



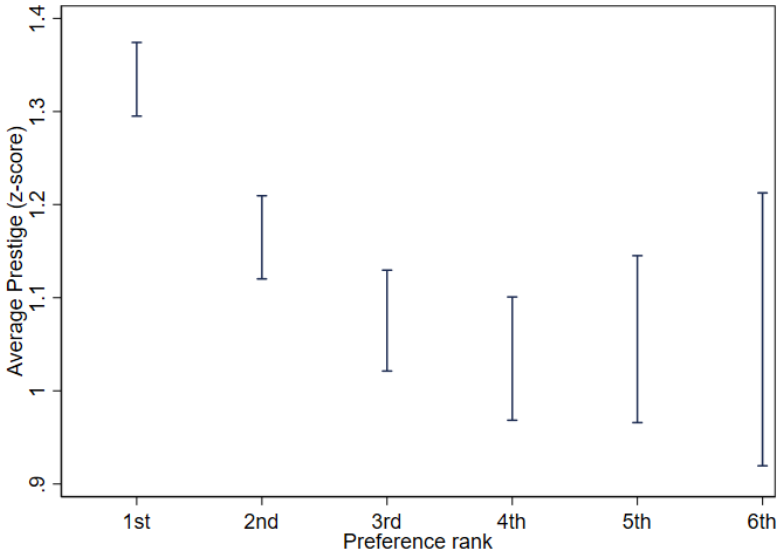
(c) CPGE applications (by gender)



(d) CPGE applications (by SES)

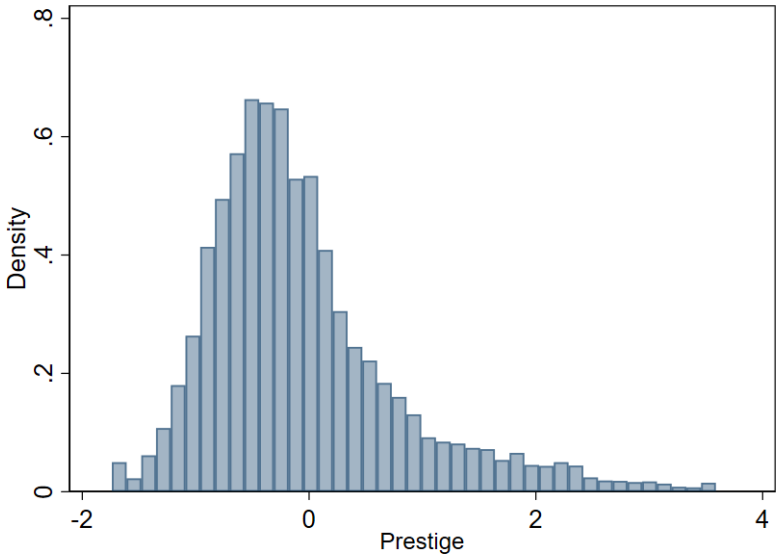
Notes: The figures show the probability that a student receives an offer from the most prestigious program in her application list on the first day of offers (to control for differences in the endogenous time when students decide to permanently accept an offer and leave the matching platform), by honor and gender/SES. In Panel (a) and (b), we consider all applications, while in Panel (c) and (d), we only consider whether a student received an offer from the most prestigious elite program (CPGE) they applied to, if any. Bars indicate 95% confidence intervals.

Figure A.6: Average program prestige by preference list rank



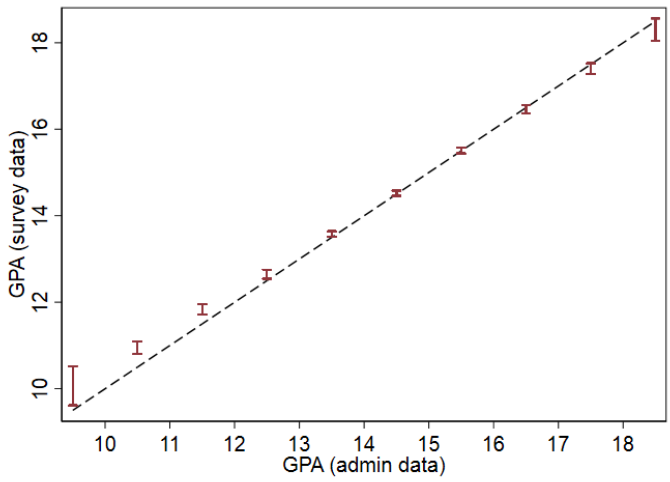
Notes: This figure shows the average prestige of the programs that students list in descending order on their preference lists, as elicited in the survey. In the survey, students were asked to name the programs they planned to apply to and rank them using score points. Inclusion of at least two programs in the survey was mandatory. The number of programs listed decreases further down the ranking, which contributes to the wider confidence intervals for lower-ranked options. Prestige is defined at the program level as the mean *bac* grade of all admitted students. Prestige is z-standardized by subtracting the mean among all programs in the dataset and dividing by their standard deviation.

Figure A.7: Distribution of program prestige



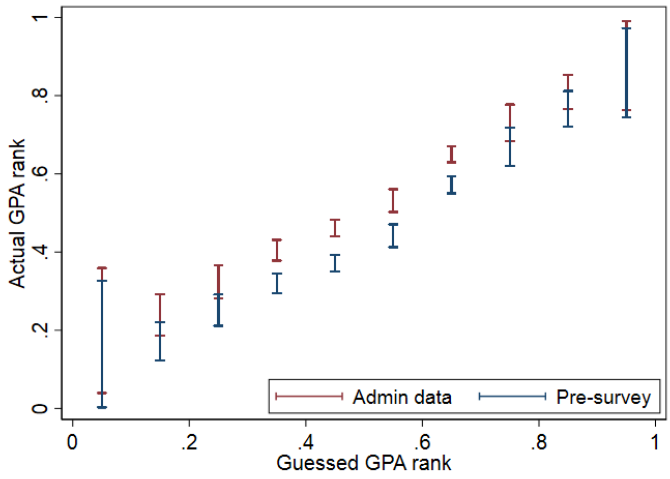
Notes: This figure shows a histogram of program prestige. The unit of observation is a program. Prestige is defined at the program level as the mean *bac* grade of all admitted students. Prestige is z-standardized by subtracting the mean among all programs in the dataset and dividing by their standard deviation.

Figure A.8: Reported GPA (survey data) vs. real GPA (admin data)



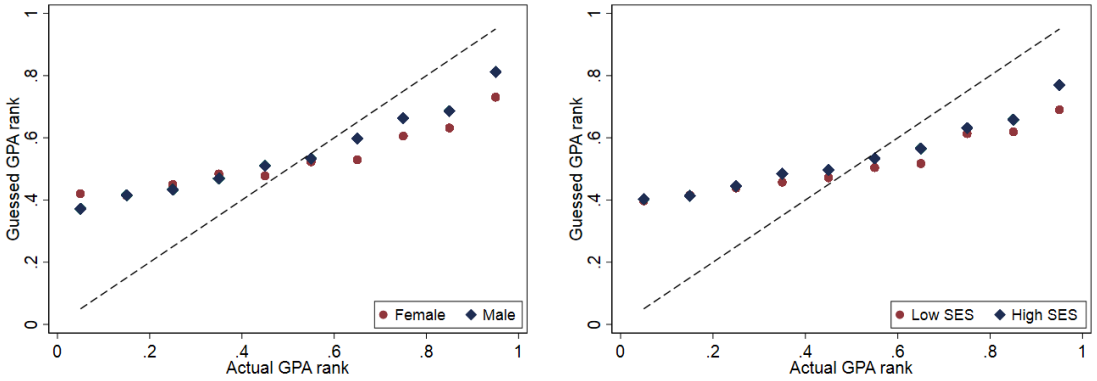
Notes: This figure shows the mean self-reported GPA in the main survey (Y-axis) by GPA in the admin data (X-axis). Students with a GPA below 10 are grouped in the leftmost category and students with a GPA above 18 in the rightmost category. The dashed line represents the 45-degree line. Bars indicate 95% confidence intervals of the mean.

Figure A.9: Student real rank in the distribution using admin vs. pre-survey data



Notes: The figure shows the mean real rank of a student (Y-axis) as a function of her guessed rank (X-axis). The real rank is calculated based on two different reference samples. We plot in red the real rank of a student in the GPA distribution defined using the administrative data for the universe of French students in the last year of the general high school track, who participated in the college admission mechanism. We plot in blue the real rank of a student in the GPA distribution defined using the sample of 1001 students we surveyed 1.5 months before our main survey. Bars indicate 95% confidence intervals of the mean.

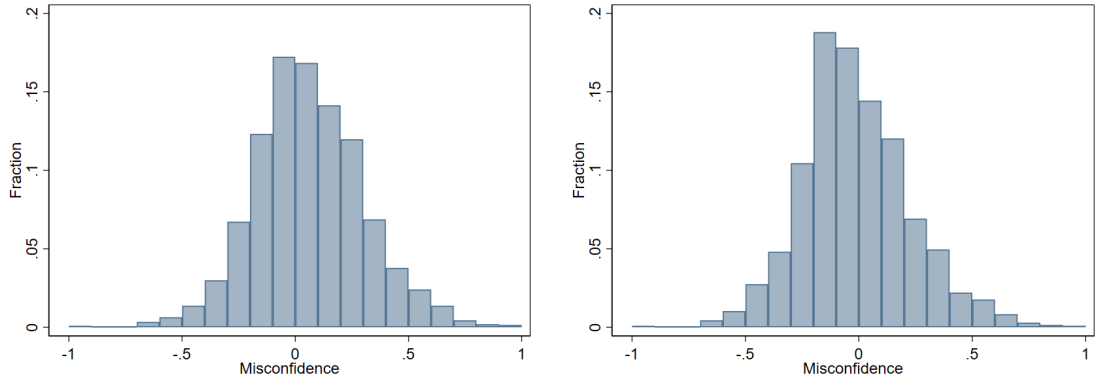
Figure A.10: Guessed GPA rank by real rank



(a) Guesses by gender (b) Guesses by SES

Notes: This figure shows the guessed GPA rank by real GPA rank (measured using the grade distribution from the pre-survey). Each dot represents mean guesses in bins of 10 ranks each. If respondents' stated guesses were accurate, they would be on the dotted 45 degree line.

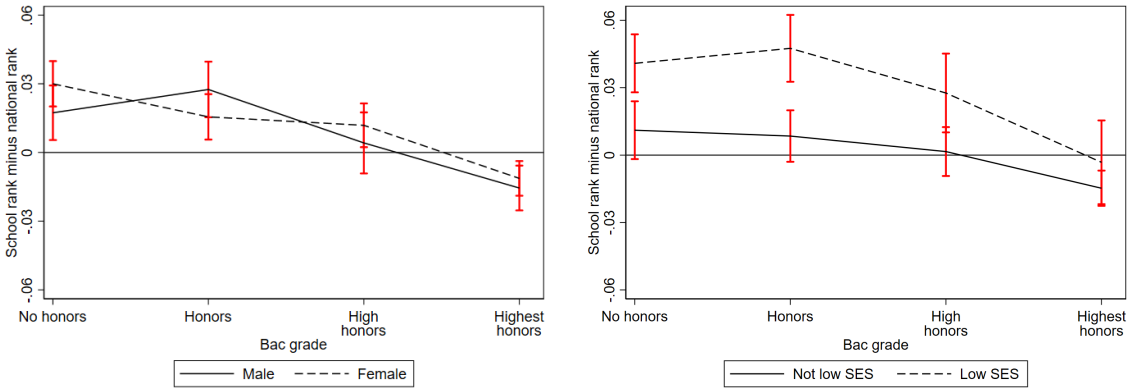
Figure A.11: Misconfidence distribution



(a) Real rank based on pre-survey (b) Real rank based on admin data

Notes: This figure shows the distribution of misconfidence (guessed rank minus real rank). In Panel A, the reference sample is based on the pre-survey. In Panel B, the reference sample is based on the administrative data.

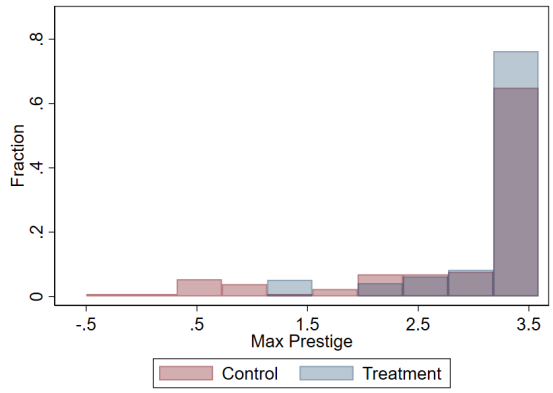
Figure A.12: Gap between school and national GPA rank by gender and SES



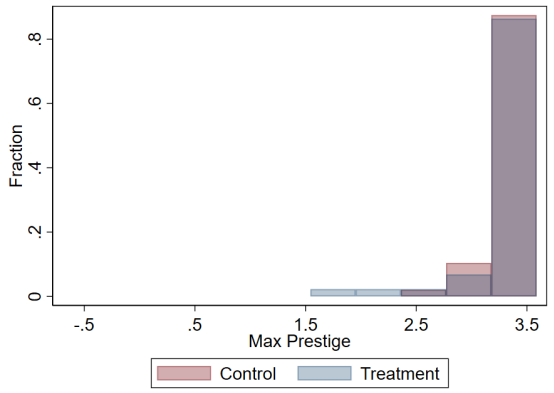
(a) Gender difference (b) Social difference

Notes: This figures show the difference between the within-school rank and the national rank by honors. Positive (negative) values mean that a student has a higher (lower) rank within their school than in the national distribution. Bars indicate 95% confidence intervals.

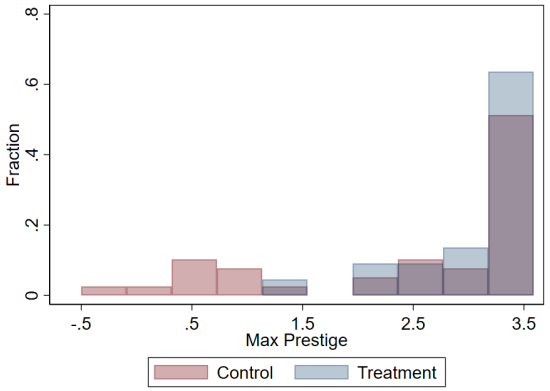
Figure A.13: Maximum prestige of application list for highest honor students



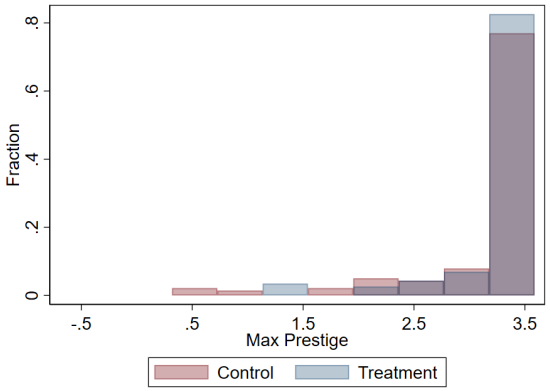
(a) Female students



(b) Male students



(c) Low-SES students



(d) High-SES students

Notes: This figure shows the distribution of the maximum prestige of the application list for students in the treated and control groups. We plot the distributions for the sample of highest honor students by gender and SES, respectively. The histograms display ten equal-sized bins.

B Alternative measures of program prestige

We measure the prestige of a program based on the high school diploma grade of the admitted students, as is common practice in the literature (MacLeod et al., 2017; Arenas and Calsamiglia, forthcoming). Other program characteristics, like program access rate, could be used to measure a program prestige. However, program access rates, that is, the ratio of the number of students admitted over the number of applicants, are less relevant for identifying aspiration gaps because some of the most difficult programs to get in (low access rate) are over-demanded due to students' specific preferences rather than the program quality or the quality of the students enrolled. For instance, some programs providing training in sports, arts, or specific health-related programs are very popular, and therefore over-demanded, without being particularly prestigious in terms of the average high school diploma grade of the admitted students. To illustrate this point, Table B.1 reports the list of the 15 most prestigious programs (column 1) and the 15 most over-demanded programs (column 2).[57] As expected, CPGEs account for the majority of the most prestigious programs. The list also includes renowned engineering schools, Sciences Po, and a few specialized public university programs.

Table B.1: List of 15 most selective programs based on prestige and access rate

	Most prestigious	Lowest access rate
1	Scientific CPGE	Bachelor - Humanities and Social Sciences
2	Scientific CPGE	Bachelor - Sport, Physical Educ. and Health
3	Literary CPGE	Applied Bachelor's Degree (BUT) - Service
4	Scientific CPGE	Bachelor - Science-Technology-Health
5	Scientific CPGE	Bachelor - Humanities and Social Sciences
6	Scientific CPGE	Applied Bachelor's Degree (BUT) - Service
7	Scientific CPGE	Bachelor - Science-Technology-Health
8	Scientific CPGE	Bachelor - Law-Economics-Management
9	Engineering school	Bachelor - Humanities and Social Sciences
10	Sciences Po	Bachelor - Science-Technology-Health
11	Scientific CPGE	Bachelor - Science-Technology-Health
12	Scientific CPGE	Bachelor - Science-Technology-Health
13	Bachelor - Law-Econ-Mgmt	Applied Bachelor's Degree (BUT) - Service
14	Scientific CPGE	Diploma in the healthcare sector
15	Engineering school	Scientific CPGE
Prestige	3.552	1.963
Access rate	0.166	0.061

Notes: This table reports the 15 most prestigious programs (according to the average *bac* grade of the admitted students) and the 15 programs with the lowest access rate. We only include programs to which at least 10 survey participants applied. The bottom row shows the average prestige and access rate of the 15 programs in the table.

While access rate is correlated with prestige, the correlation is smaller than we had expected (r=0.221 considering all programs, and r=0.360 considering programs to which survey participants applied). In particular, the programs with the lowest access rates are not those typically considered as the most prestigious. The 15 programs with

[57]The data provider does not allow to extract statistics for individual programs, but only aggregated statistics. Therefore, we cannot show the names of the institutions and programs along with the calculated prestige score.

the lowest access rate include applied university programs (BUT), diplomas in health care (i.e., nursing degrees), sports programs, and public university programs. These 15 programs have an average access rate of 6.1%, but their average prestige is only 1.96 SD. Hence, they are over-demanded, but they do not attract the best students.

Access rates are not suitable for measuring program prestige because they depend on the composition of applicants. As we show, students with high grades are more likely to apply to CPGEs, indicating that students with lower grades anticipate low admission chances. This variation in applicant pools complicates comparisons across program types. For instance, a CPGE accepting 30% of applicants is typically more prestigious than a sports license program accepting 10%, as the former attracts higher-achieving students. In contrast, our prestige measure, based on the quality of admitted students, addresses this issue and enables straightforward comparisons across program types.

We show, in Table B.2, that the results reported in the paper are robust to using program access rates as the outcome instead of program prestige, controlling for program type. We replicate the specification from Table 3 (which reports the effect of rank feedback on college applications and admissions) using as an outcome program selectivity, defined as 1 - Access rate. We use data on 2020 access rates, the year before the intervention. Higher selectivity indicates greater prestige. The outcome variable is z-standardized (mean zero, standard deviation one) for comparability. We include program-type fixed effects, comparing selectivity only within program types (e.g., CPGEs or License programs).[58] The results align with those in Table 3: misconfidence predicts the prestige of the top-listed program, but the treatment (rank feedback) mitigates this effect (p=0.085).

[58]While access rates are less suitable for comparisons *between* program types, they can effectively measure prestige *within* program types. For instance, a CPGE with a 5% access rate is more prestigious than one with a 30% access rate. Program-type fixed effects include around 30 categories such as CPGE, science-oriented university programs (License STS), and humanities-oriented university programs (License SHS).

Table B.2: Effect of rank feedback on college applications and admissions (Programs classified by access rate rather than prestige)

	College Applications	College Admissions
	Max selectivity	Selectivity
	(1)	(2)
Misconfidence	0.149*	0.118
	(0.083)	(0.157)
Rank feedback	0.036*	0.008
	(0.021)	(0.040)
Rank feedback × Misconfidence	-0.154*	-0.111
	(0.085)	(0.175)
Constant	0.696***	-0.858***
	(0.037)	(0.071)
Program-type FE	✓	✓
Real rank (pre-survey)	✓	✓
Honors FE	✓	✓
Risk preference	✓	✓
Adj. R2	0.305	0.387
Observations	2029	1607
Mean outcome	0.809	-0.481

Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the role played by confidence in student college choices. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability distribution. Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. We define the misconfidence and real rank variables using the GPA distribution from the sample of students in the pre-survey. In Column (1), the dependent variable is the z-standardized maximal selectivity (1 − access rate) of the application list, in Column (2), the outcome is the selectivity of the final match. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

C Do programs weigh high school grades?

In this section, we investigate the role of high schools for admission chances, conditional on grades. It is a common belief that top programs reweigh grades depending on the high school in which the grades were obtained.

Since such differential weights are more likely to play a role for the most prestigious programs, we focus on the programs who belong to the top 10th percentile of the prestige distribution. We regress a dummy for receiving at least one offer from a top10 prestige program on the first day on student GPA. Then, we add high school fixed effects. To ensure that high school fixed effects are identified, we only include high schools from which at least ten students applied to a program in the top 10 percent of most prestigious programs. This restriction allows us to estimate 2,337 high school fixed effects (out of 2,800 high schools in which at least one student applied to a top 10 prestige program). We estimate the following specification:

$$\text{Offer 1st day}_{ik} = \beta_0 + \beta_1 \times GPA_{ik} + \theta_k + \epsilon_{ik} \tag{6}$$

where the dependent variable indicates whether student i in high school k receives at least one offer from a top 10 prestige program on the first day of the admission mechanism.[59]

We report the regression results in Table C.1. The adjusted R^2 of the specification that only contains high-school fixed effects is equal to 0.032. The adjusted R^2 of the specification including only the GPA indicators is equal to 0.391. The outcome being a dummy variable, we expect the R^2 to be relatively low, and we are mainly interested in the increase in R^2 between specifications. In Column (3), we add high-school fixed effects and find that the R^2 increases to 0.411.

To assess the importance of grade reweighting, we calculate how many high-school fixed effects are significant. The significance of each high-school fixed effect depends on the reference high-school (its admission probability conditional on grades, as well as its variance and sample size). To assess how many high schools have exceptionally high and low fixed effects, we need to use a reference high-school with an average admission probability. We therefore run regression (6) 58 times using all high-schools that have fixed effects closest to zero (between -0.001 and +0.001) subsequently as reference schools.[60] We then average the t-statistic of the high school fixed effects over the 58 regressions.

Only 7.9 percent of fixed effects are significant on the 5% level and 13.1 percent of fixed effects are significant on the 10% level. Hence, the number of significant fixed effects is not much higher than what would be expected by chance. Some very prestigious high-schools have significant positive fixed-effects, partly driven by CPGEs who preferentially admit students who went to high school in the same facilities. On the other hand, some high schools have significant negative fixed effects, in particular international schools abroad and distant education institutions. However, for the vast

[59] We only include offers on the first day since later offers depend on the decision of the applicant to wait for other offers.

[60] We use the predicted fixed effects after `xtreg` in Stata. These predicted fixed effects are constrained to sum to one across all observations.

majority of high schools, GPA reweighting does not appear to be systematic and prevalent.

Table C.1: Relationship between offer probability, GPA, and high-school fixed effects

	Offer from a top 10% prestige program		
	(1)	(2)	(3)
GPA 10-11		0.000	-0.000
		(.)	(0.001)
GPA 11-12		0.000	-0.001
		(0.000)	(0.001)
GPA 12-13		0.001***	-0.000
		(0.000)	(0.001)
GPA 13-14		0.003***	0.001
		(0.000)	(0.001)
GPA 14-15		0.025***	0.023***
		(0.001)	(0.001)
GPA 15-16		0.120***	0.120***
		(0.002)	(0.002)
GPA 16-17		0.379***	0.384***
		(0.003)	(0.004)
GPA 17-18		0.698***	0.711***
		(0.005)	(0.005)
GPA >18		0.858***	0.893***
		(0.007)	(0.007)
Constant	0.117***	-0.000	-0.001
	(0.001)	(.)	(0.001)
High-school FE	✓		✓
Adj. R2	0.032	0.391	0.411
Observations	180,368	180,368	180,368
Outcome mean	0.117	0.117	0.117

Notes: This table reports the relationship between the probability of receiving an offer (on the first day) from a program on student GPA dummies (reference is GPA below 10) and high-school fixed effects. The dependent variable is an indicator for receiving at least one offer from a top 10% prestige program on the first day. GPA is the average GPA from the first five trimesters (which are available at the time of application). We only consider schools in which at least 10 students applied to at least one top 10% prestige program. Standard errors reported in parentheses are clustered at the student level. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

D Data collection - Main survey

We conducted a large-scale survey of students participating in the French college admission procedure in 2021. We recruited our sample using social media ads (Instagram, Snapchat, and Facebook). Individuals who clicked on the ad were redirected to the Qualtrics survey.

On the landing page, respondents were informed of the survey and asked for consent regarding the raffle terms, the privacy policy, and the merge of their data with administrative data. Of the 14,590 respondents that consented to participate, 48% dropped out on the first page of the survey when asked for their name, demographics, and contact details (see Table D.1). Hence, the reasons for dropping out are unrelated to the topic of the survey.[61] Another 24% dropped out when asked to state the programs (city, institution, and program) they planned to apply for in Parcoursup in free-text form. In the end, 3,584 students entered their application list and provided a guess on their admission chances (the following step). These students were randomized into treatment or control.

While the completion rate may appear low, it is comparable to earlier studies and may be due to a number of factors (cf. Allcott et al., 2020). First, the sample does not consist of participants who signed up for a survey panel and, thus, showed a general interest in sharing their data. Participants may have clicked on the link out of curiosity, but decided to opt out after finding out that the survey asked for personal information. Second, respondents clicked on the ad while browsing social media. They may not have been prepared to complete a 12-minute survey that contained a number of relatively tedious free-text responses (such as the application list). Although we tried to keep the survey concise, it is arguably less entertaining and requires a longer attention span than the content typically consumed on social media.

Among the students who completed the survey approximately one third were recruited via Instagram and Facebook, and approximately two thirds via Snapchat. A few participants were recruited via alternative channels.[62]

Among the 3,584 complete responses, we removed duplicate entries that we identified based on the mail address, phone number, and name, leading to a sample of 3,508 valid observations.[63]

[61] Subjects were informed that all analyses would be anonymized and that their personal information would only be used to match their responses to the administrative records and to contact them in case they had won a gift card.

[62] We bought a few ads on Twitter and Google, but rapidly stopped these ads as the response rate from our target group was low. We also had a banner campaign on the website l'Etudiant (which provides information targeted at French high school students). The response rate was also low.

[63] Some students may have taken the survey multiple times to maximize their chances of winning gift cards (although we explicitly stated in the consent form that students could only enter the raffle once). If a respondent completed the survey more than once, we considered their pre-treatment answers from the first entry and their post-treatment answers from the final entry. The treatments are cumulated, that is, a respondent who received one treatment in the first attempt, and another treatment in the second attempt, is treated as receiving both treatments.

Figure D.1: Social media ad

Notes: The figure shows the social media ad we used to recruit students. The ad targets students in the final year of high school who are about to submit their college applications to the Parcoursup platform. The ad offers the chance to win a 100 Euro giftcard for completing the survey.

Matching survey and admin data. To match the survey and administrative data, we asked survey respondents for their national student number (INE).[64] Based on the INE, we matched 1,730 respondents. For students who did not provide their INE, we matched the survey and admin data based on the school, postal code, birth date, and gender. When these variables did not uniquely identify an observation, we compared the application lists reported in the survey and in the admin data of the potential matches. Using this combination of characteristics, we matched another 1,537 respondents with the administrative data. In total, this procedure allowed us to match 3,267 respondents successfully. The students we could not match are excluded from our analysis.

As specified in the pre-registration of the misconfidence hypotheses, we focus on students in the general high school track (*Bac général*) because treated students receive feedback on their rank compared to other *Bac général* students. Restricting the sample to *Bac général* students yields our final sample of 2,034 respondents.

In Table D.2, we study whether attrition at different steps of the survey is correlated with observable characteristics. Column (1) shows that females are more likely to drop

[64]The INE is an 11-digit, unique identifier which is, for example, given on student report cards. As students also needed the INE to register on the college application platform (Parcoursup), many of them knew where to look it up.

out after entering demographics.[65] Column (2) shows that 87% (0.459/0.527) of those who drop out after entering demographics, drop out on the next page when asked to enter their application list. However, dropping out at this stage is not correlated with gender or age. Column (3) shows that females are more likely to drop out between entering the application list and the rank elicitation. According to Column (4), older respondents are more likely to drop out when asked for their guessed rank in the GPA distribution. However, only 46 respondents drop out when asked for the guessed rank. Since the treatment was provided directly after the rank elicitation, respondents after this step are part of the sample.

Table D.1: Sample size of main survey

Number of students	Step
14,969	Started questionnaire
14,590	Consented to participate
7,577	Entered demographics
4,101	Entered application list
3,584	Assigned to treatment
3,508	Sample without duplicates
3,267	Matched to admin data
2,034	In *bac général* (final sample)

[65] Gender and age are the only variables that we can use because other variables are either elicited later in the survey or taken from the administrative data (e.g., SES). However, since the national student number is only elicited at the end of the survey, participants who do not finish the survey are not matched.

Table D.2: Attrition analysis

	After demographics (1)	At application list (2)	Between list and rank guess (3)	At rank guess (4)
Female	0.020*	0.008	0.026**	-0.001
	(0.012)	(0.012)	(0.010)	(0.004)
Age	0.010	0.008	-0.003	0.009***
	(0.007)	(0.007)	(0.007)	(0.002)
GPA				-0.001
				(0.001)
Technical HS track				0.007
				(0.005)
Professional HS track				-0.005
				(0.005)
Constant	0.336***	0.311**	0.146	-0.133***
	(0.127)	(0.127)	(0.114)	(0.046)
Mean outcome	0.527	0.459	0.115	0.013
Adj. R2	0.000	-0.000	0.001	0.005
Observations	7576	7576	4100	3629

Notes: This table reports correlations between survey dropout and student characteristics, such as gender age, GPA, and high school track (technical or professional). The dependent variable is a binary variable indicating whether a student did not finish the survey. We report robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

E Data collection - GPA survey

Data collection. Between the 20th of January and 1st of February 2021, we surveyed 1,001 high school students who were planning to participate in Parcoursup 2021. The goal of the pre-survey was to form a reference group to which we could compare the grades of students in the main survey. We recruited students via ads on Instagram and Facebook (see Figure E.1) targeted at 17 to 18-year old French users. The ad offered the chance to win a 50 Euro gift card for completing a 3-minute survey. On the landing page, we pre-screened students based on whether they were in the final year of high school, whether they planned to take part in Parcoursup in 2021, and whether they were at least 16 years old. After deciding to use only students in *bac général* for the reference group, we also added a corresponding screening question.[66]

Sample size. Table E.1 shows that 4,464 students started the questionnaire, of whom 2,600 fulfilled the screening criteria, and 1,264 completed the questionnaire. After removing students who were not in *bac général*, duplicates, and invalid responses (e.g., a grade point average of 0.0), the final sample we use to calculate the grade distribution consists of 1,001 students.

Sample representativeness. Among the students, 57.4% were female, with an average age of 17.4 years, and an average GPA of 14.0.[67] These characteristics are very similar to our main survey and the population in the admin data (cf. Table A.1). Figure A.9 further shows that the grade distribution of students in the pre-survey and in the administrative data is also close, especially among top students.

Table E.1: Sample size of pre-survey

Number of students	Step
4,464	Started questionnaire
2,600	Passed pre-screening
2,523	Consented to participate
1,311	Entered demographics
1,264	Completed survey
1,001	In *bac général* and valid

[66] On January 26, more than 70% of respondents reported doing a *bac général*. We realized it would be difficult to obtain a meaningful sample size for *bac technologique* and *bac professionelle*. Hence, we decided to focus the reference group on *bac général* students.

[67] We do not know the share of low-SES students in this sample as we cannot match the pre-survey to the administrative data.

Figure E.1: Screenshot of ad for pre-survey

Notes: This screenshot shows the Facebook ad for the pre-survey. It addressed students in the final year of high school who were planning to participate in Parcoursup 2021, and offered the chance to win a 50 Euro giftcard for completing a 3-minute survey. The Instagram ads used the same picture and text.

F Further pre-registered outcomes (for online appendix)

In the pre-registration, we specified the following additional hypotheses, which are not the focus of the present paper and which are therefore reported in the online appendix:

- The treatment decreases the impact of underconfidence on acceptance of the first offer.
- The treatment increases the length of the submitted list of overconfident students.
- The treatment decreases the rank of the outcome bet for underconfident students and increases it for overconfident students

F.1 First offer acceptance

We conjectured that self-confidence affects the probability of accepting an early offer. Remember that on the first day of the mechanism, programs send out offers to the top-ranked applicants up to their capacity. Declined offers are sent out to the next-ranked applicants. This means that students tend to receive "better" offers (where they are more likely to be marginally accepted) later in time. We hypothesized that underconfident students are more likely to accept an early offer because they do not expect to receive a better offer later.

To study the propensity to accept an early offer, we define the first offer bonus on the individual level as follows:

$$\text{First offer bonus}_i = \text{I(accept first)}_i - \frac{\text{number offers on day of first offer}_i}{\text{total number of offers}_i} \tag{7}$$

The first offer bonus is the difference between an indicator for accepting the first offer and the share of offers an individual received on the same day as the first offer. The first offer bonus approaches 1 if an individual accepts the first offer, although most of her offers arrived after the first offer. It approaches -1 if the individual does not accept the first offer and most of her offers arrived together with the first offer.

In line with the incentives of the mechanism (i.e., better offers arriving later), the first offer bonus is on average negative (-0.155) and significantly smaller than zero ($p < 0.01$).

In Table F.1, we regress the first-offer bonus on underconfidence and treatment indicators. The underconfidence coefficient shows that, in the control group, underconfidence is positively correlated with a higher first-offer bonus. That is, underconfident students are more likely to accept an early offer. We find that the treatment reduces the impact of underconfidence on the first offer bonus, but the treatment effect is not statistically significant ($p = 0.160$).

Table F.1: Regression of first offer bonus on underconfidence and treatment dummy

	(1) First offer bonus
Underconfidence	0.300***
	(0.104)
Grade feedback	0.000
	(0.019)
Grade feedback	
× Underconfidence	-0.188
	(0.134)
Mean first offer bonus	-0.156
Real rank (pre-survey)	✓
Honors FE	✓
Risk preference	✓
Observations	1793

Notes: The table reports OLS regression estimates. The dependent variable is the first-offer bonus as defined in Equation (7). Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

F.2 Number of applications

We hypothesized that overconfident students would apply to fewer programs and that providing feedback to overconfident students would increase the length of their submitted list.

In the first column of Table F.2, we regress the number of applications on misconfidence, controlling for real rank. Contrary to the hypothesis, more confident applicants seem to apply to more programs and this seems to be driven by underconfident students applying to fewer programs. However, this may be driven by the fact that underconfident students are less likely to apply to elite track programs (CPGE). As described in Section 2.1, students who apply to CPGE can apply to many sub-programs, which is not the case for public university programs. Hence, a student who is confident enough to apply to CPGE may apply to more programs, just because their application limit is less restricted. To rule out this possibility, we exclude all students who applied to at least one CPGE in Column 2 of Table F.2. Interestingly, the misconfidence coefficients switch signs and being more confident is associated with fewer applications (but not significantly so).

In Table F.3, we regress the number of applications on misconfidence interacted with the treatment indicator. As before, in Column 1, it appears as if more confident students apply to more programs and the treatment reduces the impact of misconfidence on applications. However, when we exclude students who apply to CPGE in Column 2, the treatment effect is no longer negative, but positive and close to zero.

Hence, we do not find support for the hypothesis that miscalibrated confidence affects the number of applications once we control for the mechanical effect through a change in CPGE applications. Moreover, our treatment has no effect on the number of applications.

Table F.2: Regression of number of applications on misconfidence (only control group)

	(1) Number applications	(2) Number applications
Panel A: Effect of misconfidence		
Misconfidence	1.664	-0.886
	(1.228)	(1.380)
Panel B: Effect of underconfidence		
Underconfidence	-3.115*	1.177
	(1.731)	(1.976)
Panel C: Effect of overconfidence		
Overconfidence	0.846	-0.813
	(1.805)	(1.882)
Sample	All	No CPGE
Real rank (pre-survey)	✓	✓
Honors FE	✓	✓
Risk preference	✓	✓
Observations	1047	763

Notes: The table reports OLS regression estimates. The dependent variable is the number of applications (wishes and sub-wishes). Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

Table F.3: Regression of number of applications on misconfidence and treatment dummy

	(1) Number applications	(2) Number applications
Panel A: Misconfidence		
Misconfidence	1.542	-0.742
	(1.032)	(1.138)
Grade feedback	0.551**	0.221
	(0.268)	(0.275)
Grade feedback		
× Misconfidence	-1.670	0.128
	(1.113)	(1.129)
Sample	All	No CPGE
Real rank (pre-survey)	✓	✓
Honors FE	✓	✓
Risk preference	✓	✓
Observations	2034	1505

Notes: The table reports OLS regression estimates. The dependent variable is the number of applications (wishes and sub-wishes). Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

F.3 Rank of prediction of final assignment

In the survey, we asked the students for their preference list regarding the programs they intended to apply for. We hypothesized that underconfident students would tend to bet on a program that they stated they preferred less, while overconfident students would bet on a program that they stated they preferred more.

In Table F.4, we regress the rank of the guessed outcome in the preference list on misconfidence. Rank 1 is the most preferred program and higher values mean that programs are preferred less. We find higher degress of under- and overconfidence both lead to betting on less preferred programs, but the coefficients are far from statistically significant. Moreover, we find that real rank does not predict the rank of the guessed outcome, suggesting that the selection of programs that students make already factors in their admission chances. These findings are in line with models of expectation-based loss aversion, in which agents rank those programs at the top of their preference list that they think they can attain (Meisner and von Wangenheim, 2023b; Dreyfuss et al., 2022c). Meisner (2023b) shows that such a pattern can emerge from disliking rejection and enjoying the confirmation of being accepted at a top-ranked program.

In Table F.5, we regress the rank of the guessed outcome on misconfidence interacted with the treatment indicator. At first glance, it appears that the treatment makes students bet on programs that are less preferred according to their initial preference list, irrespective of their level of misconfidence. However, Table F.6 provides suggestive evidence that the initial preference list should not be taken at face value when assessing students' actual preferences. Column (2) shows that the treatment leads underconfident students to bet on more prestigious programs and overconfident students to bet on less prestigious programs (although not significantly so). Taken together, these results suggest that some underconfident students actually prefer more prestigious programs, which they listed lower in their initial preferences, and begin betting on them once the feedback makes them believe they have a chance of receiving an offer. Moreover, it is important to note that underconfident students who only began to consider a prestigious program after receiving feedback could not bet on it, as the bet had to be selected from their initial preference list.

Table F.4: Regression of rank of guessed outcome on misconfidence (only control group)

	(1)
	Rank of guessed outcome
Panel A: Effect of misconfidence	
Misconfidence	-0.059
	(0.206)
True rank	-0.039
	(0.230)
Panel B: Effect of underconfidence	
Underconfidence	0.346
	(0.368)
True rank	-0.085
	(0.214)
Panel C: Effect of overconfidence	
Overconfidence	0.140
	(0.249)
True rank	0.064
	(0.211)
Real rank (pre-survey)	✓
Honors FE	✓
Risk preference	✓
Observations	1032

Notes: The table reports OLS regression estimates. The dependent variable is the rank of the guessed outcome in the respondent's preference list. The lower the rank, the more the individual prefers the program according to their preference list. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

Table F.5: Regression of rank of guessed outcome on misconfidence and treatment dummy

	(1)
	Rank of guessed outcome
Panel A: Misconfidence	
Misconfidence	-0.046
	(0.177)
Grade feedback	0.112**
	(0.050)
Grade feedback	
× Misconfidence	0.021
	(0.214)
Real rank (pre-survey)	✓
Honors FE	✓
Risk preference	✓
Observations	1990

Notes: The table reports OLS regression estimates. The dependent variable is the rank of the guessed outcome in the respondent's preference list. The lower the rank, the more the individual prefers the program according to their preference list. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

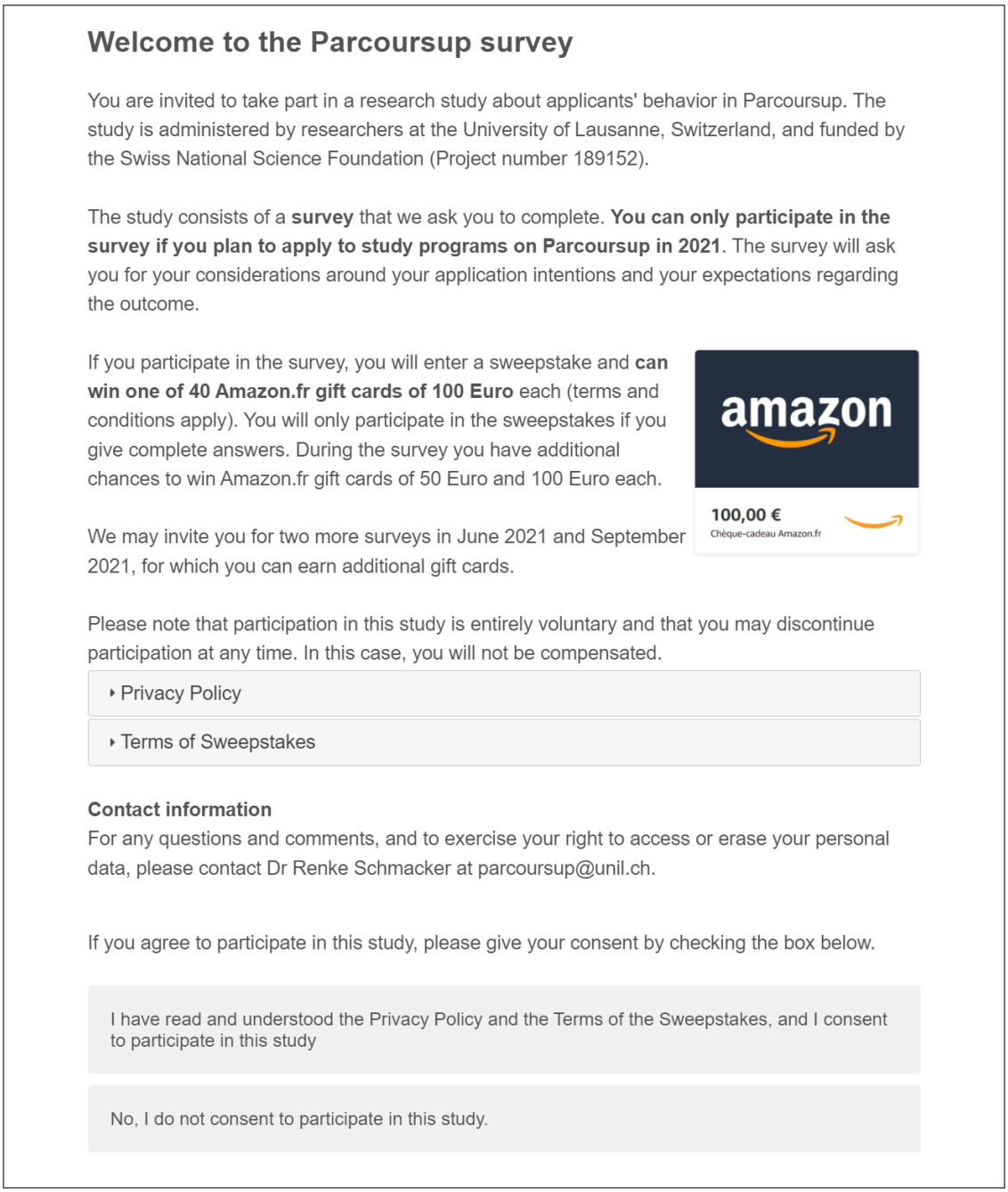
Table F.6: Effect of confidence and feedback treatment on the prestige of guessed match

	(1) Prestige of bet	(2) Prestige of bet
Misconfidence	0.536***	
	(0.196)	
Grade feedback	0.046	0.034
	(0.053)	(0.080)
Grade feedback		
× Misconfidence	-0.251	
	(0.208)	
Underconfidence		-0.734*
		(0.398)
Grade feedback		
× Underconfidence		0.316
		(0.545)
Overconfidence		0.388
		(0.257)
Grade feedback		
× Overconfidence		-0.195
		(0.307)
True rank	✓	✓
Honors FE	✓	✓
Risk preference	✓	✓
Adj. R2	0.262	0.261
Observations	1829	1829

Notes: Grade feedback is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability distribution. Misconfidence is the difference between a student's guessed and real rank. This variable ranges from -1 (for full underconfidence) to 1 (for full overconfidence). A value of 0 corresponds to students who correctly guess their rank in the ability distribution. We define the misconfidence and real rank variables using the GPA distribution from the sample of students in the pre-survey. The dependent variable is the prestige of the guessed outcome (based on the incentivized bet on the final match). Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

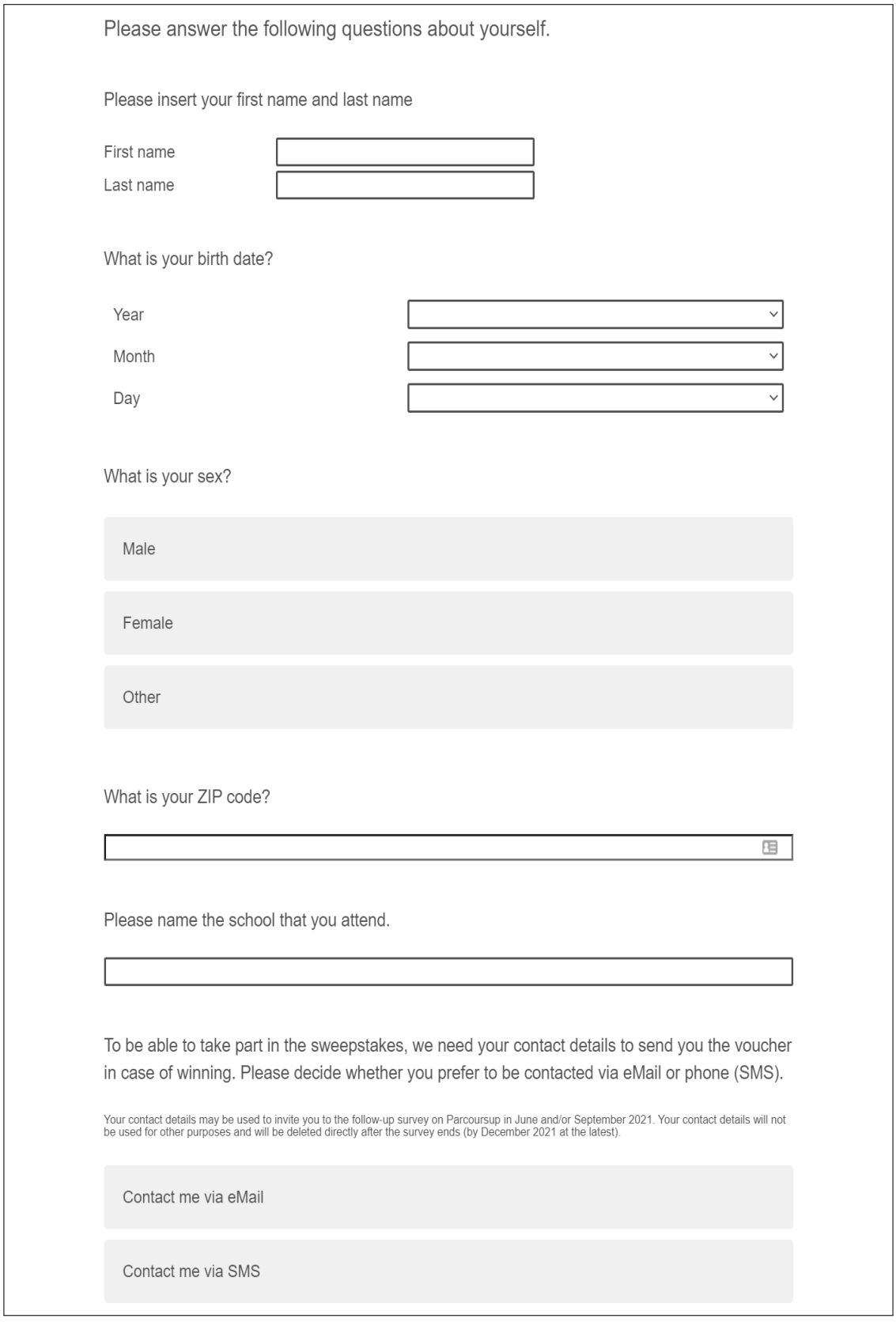
G Main Survey Instructions (translated from French)

Figure G.1: Screenshot of welcome screen and consent form



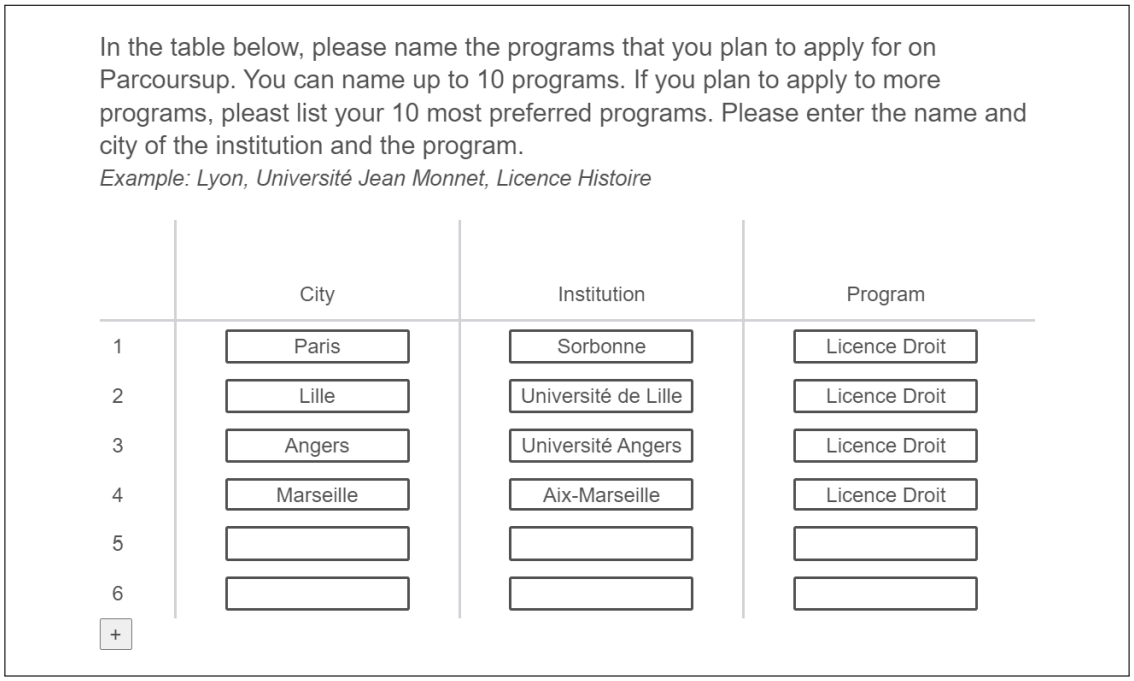
Notes: Subjects were welcomed and asked to consent to the privacy policy and terms of participation. The privacy policy informed participants that their responses would be matched to administrative data and pseudonymized afterwards.

Figure G.2: Screenshot of demographic questionnaire



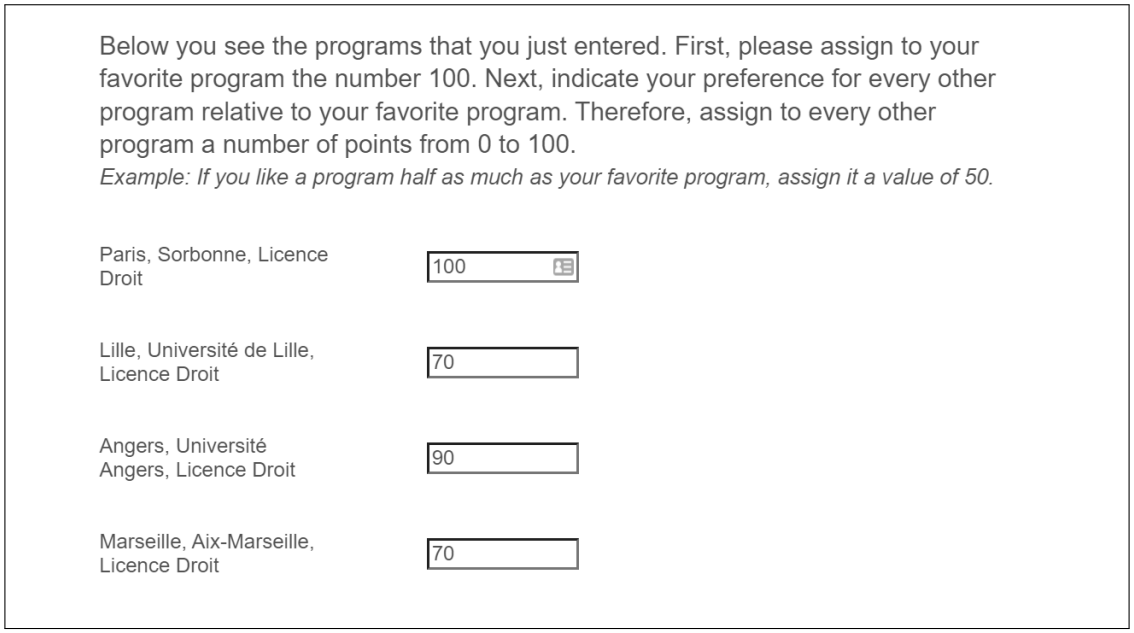
Notes: Subjects were asked for their demographic characteristics and contact details.

Figure G.3: Screenshot of application list elicitation



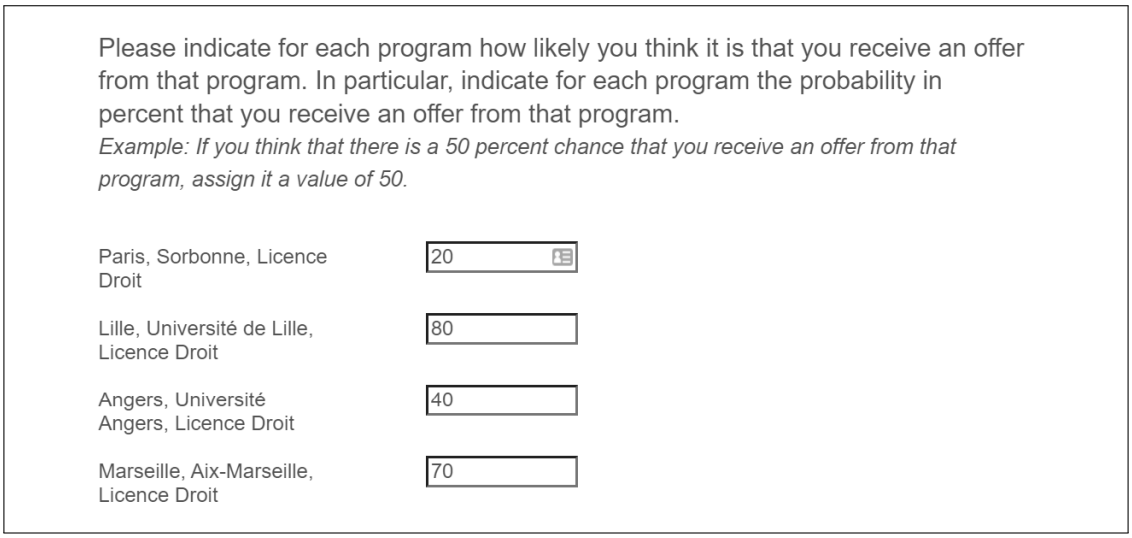
Notes: Subjects were asked to indicate the programs they planned to apply to on Parcoursup. By clicking on [+], they could extend the list and enter a maximum of 10 programs.

Figure G.4: Screenshot of preference elicitation



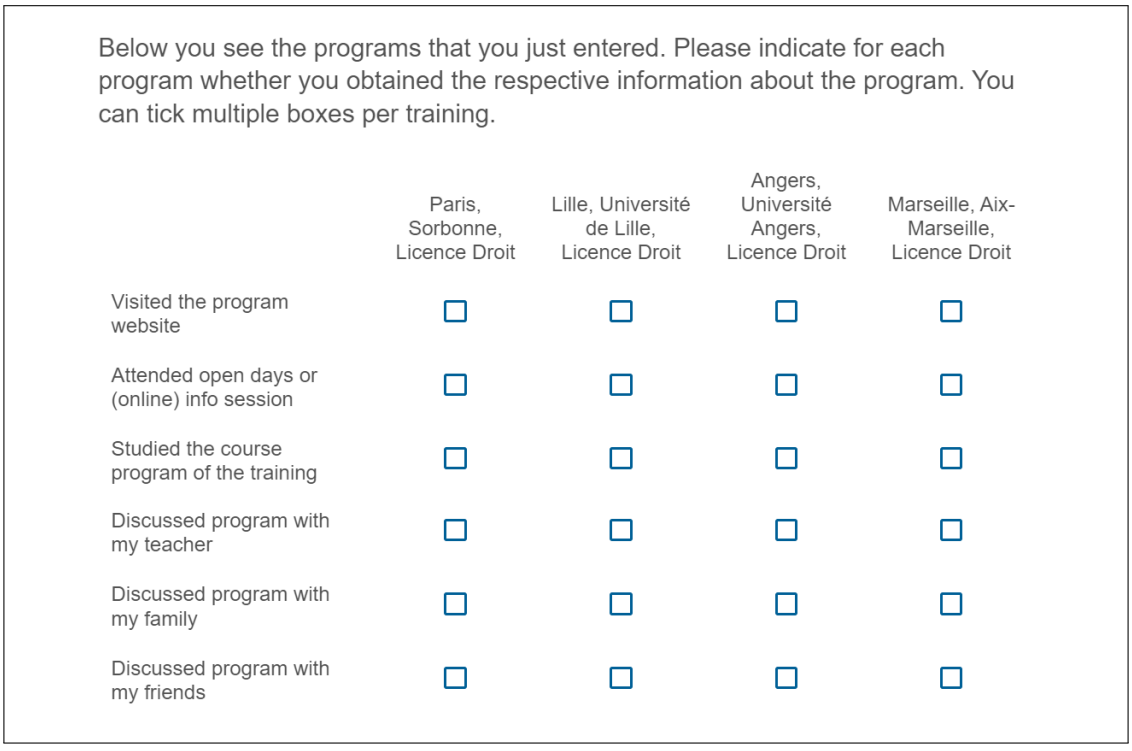
Notes: Subjects were asked for their relative preferences for the programs they had indicated on the previous screen.

Figure G.5: Screenshot of belief elicitation about offer probability



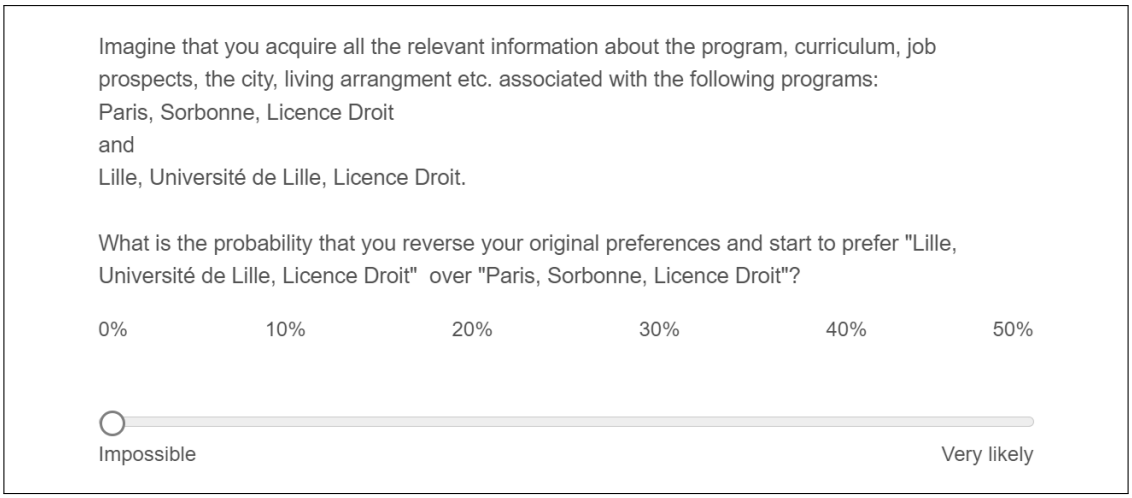
Notes: Subjects were asked for their beliefs about receiving an offer from the programs they had indicated in Figure G.3.

Figure G.6: Screenshot of question for information acquisition



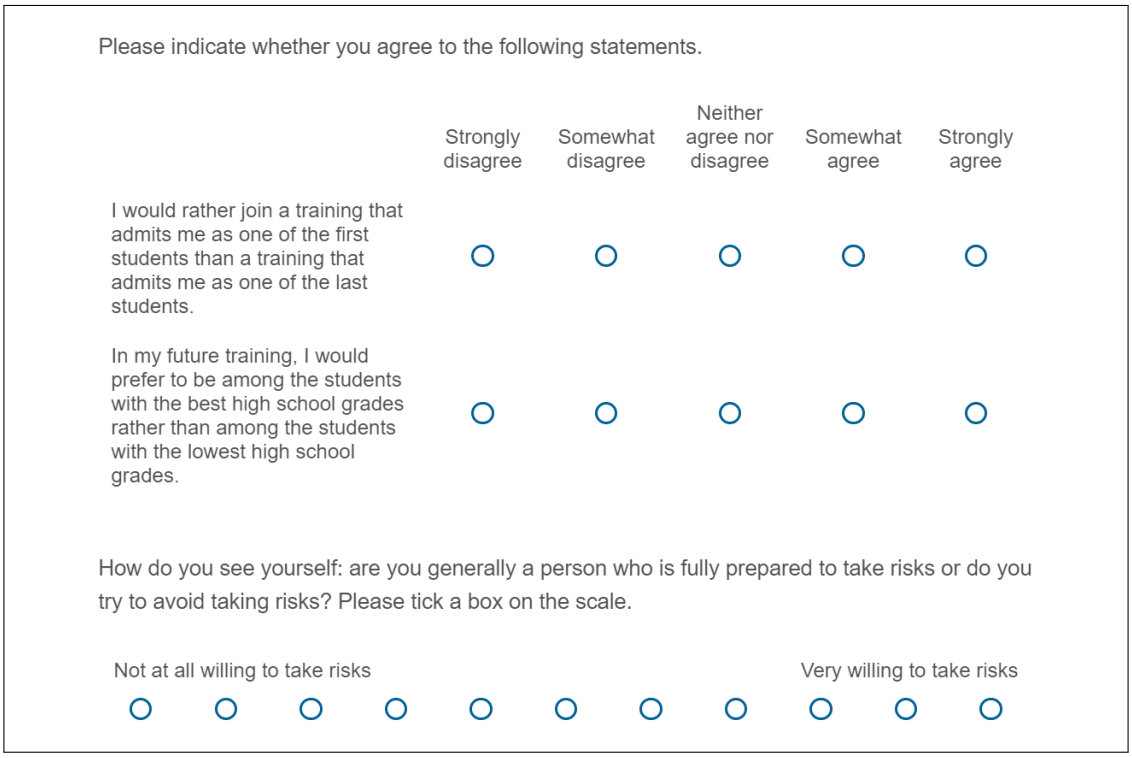
Notes: Subjects were asked whether they had acquired information on the programs they had indicated on the screen in Figure G.3.

Figure G.7: Screenshot of preference certainty question



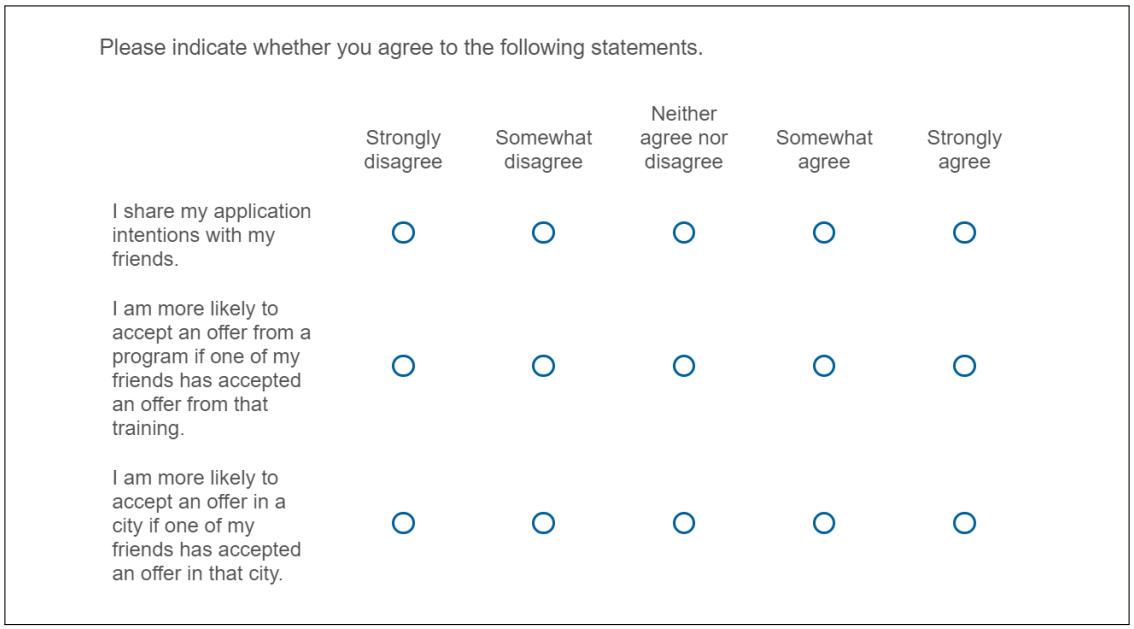
Notes: Subjects were asked how likely it was that they would start to prefer their second most-preferred program over their most-preferred program once they had acquired all the necessary information.

Figure G.8: Screenshot of question for importance of being among the best and risk



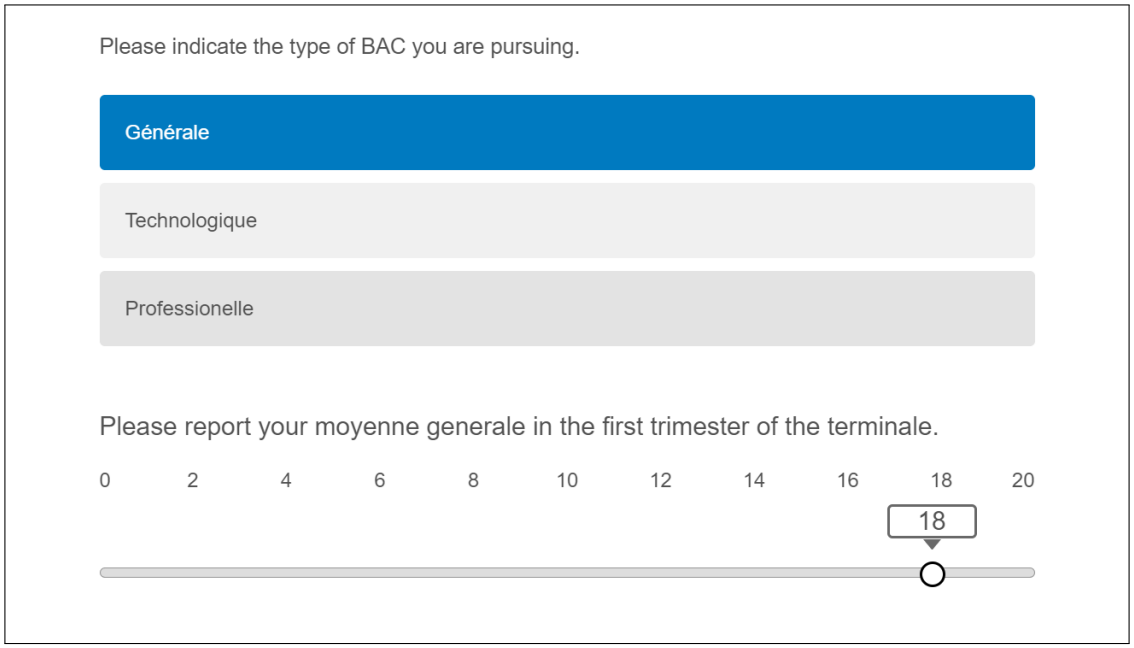
Notes: Subjects were asked for the importance of being among the best students and for their risk preferences.

Figure G.9: Screenshot of question for coordination with peers



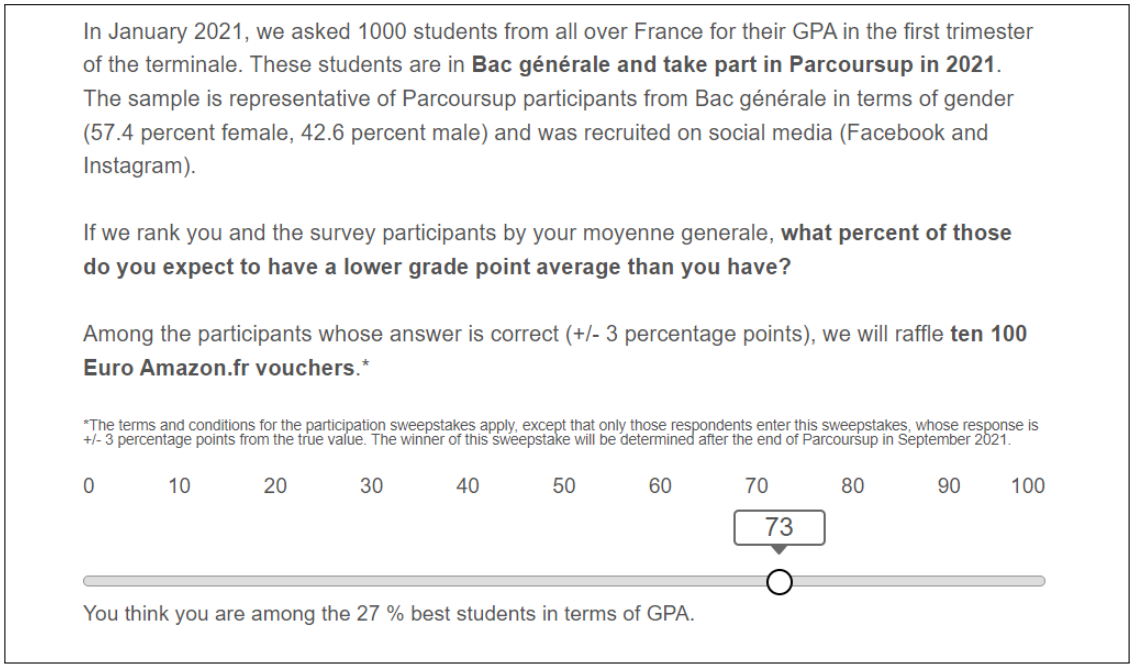
Notes: Subjects were asked whether they had coordinated their applications with their peers.

Figure G.10: Screenshot of question for GPA and type of *bac*



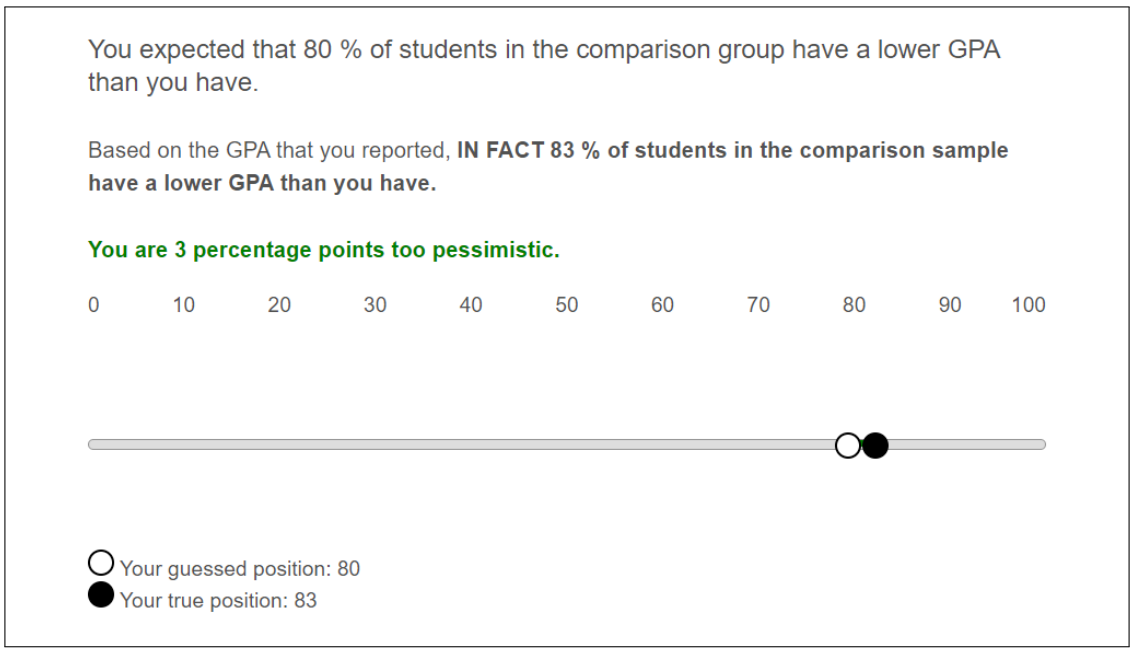
Notes: Subjects were asked for their *bac* type and their GPA in the previous trimester.

Figure G.11: Screenshot of question for rank in the GPA distribution



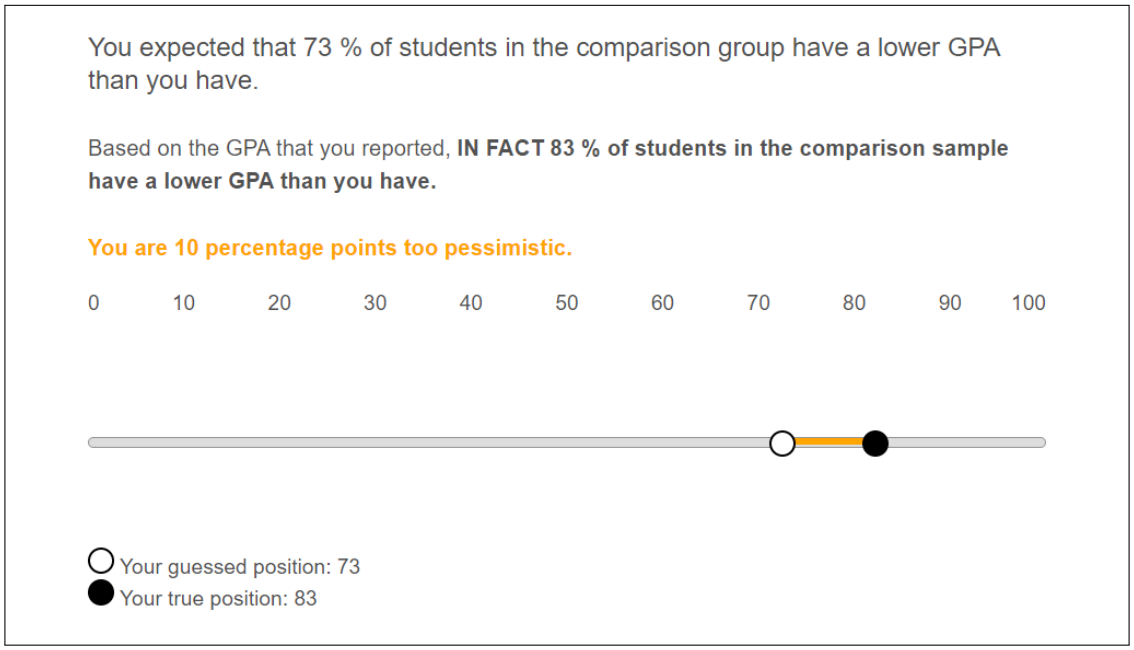
Notes: Subjects were incentivized to guess their rank in the GPA distribution.

Figure G.12: Screenshot of grade feedback (green)



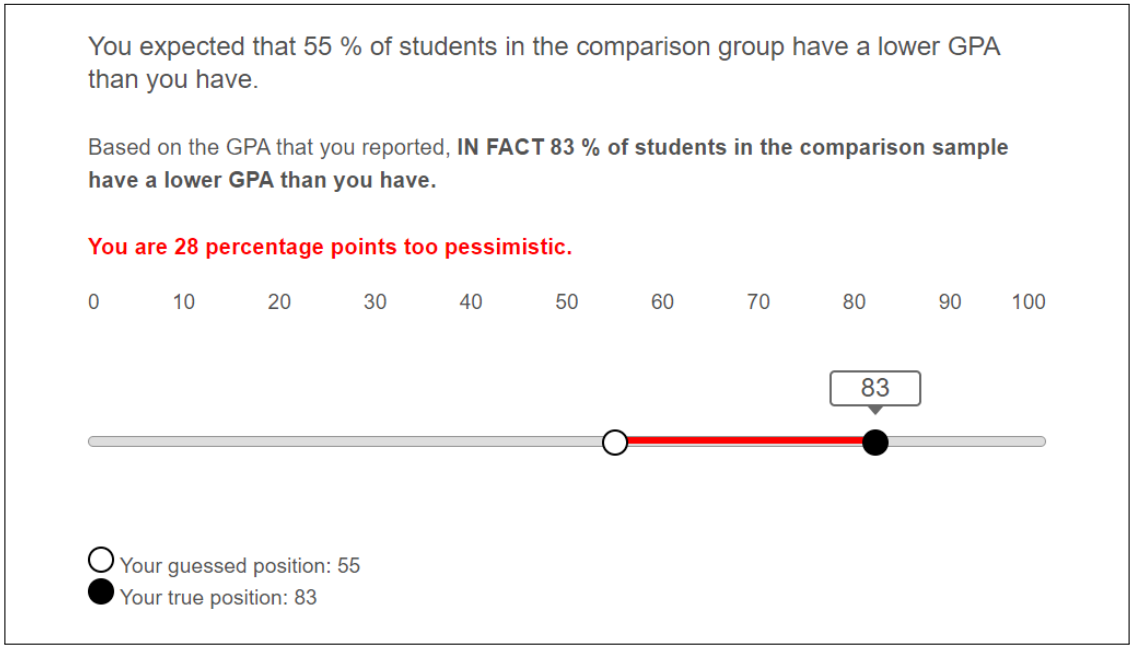
Notes: In this example, the subject underestimated their rank by less than 3 percentiles.

Figure G.13: Screenshot of grade feedback (yellow)



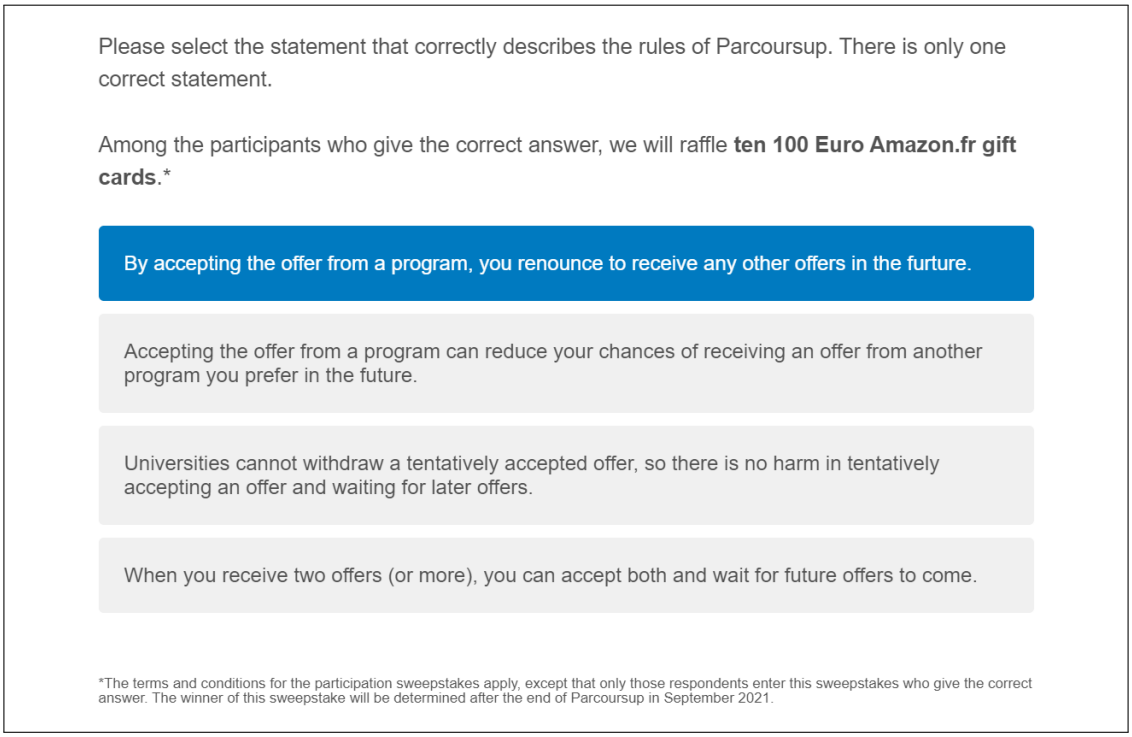
Notes: In this example, the subject underestimated their rank by 10 percentiles.

Figure G.14: Screenshot of grade feedback (red)



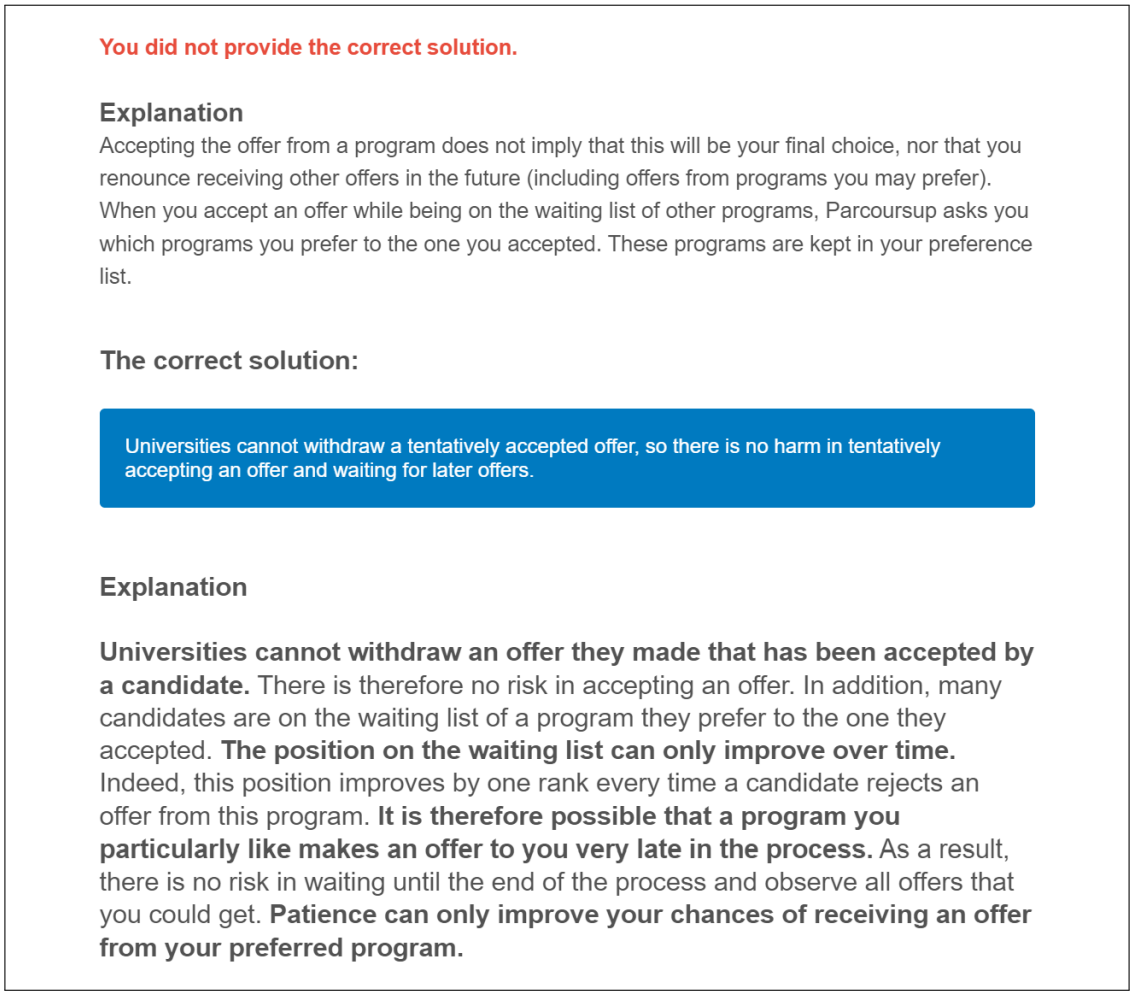
Notes: In this example, the subject underestimated their rank by more than 10 percentiles.

Figure G.15: Screenshot of mechanism knowledge quiz



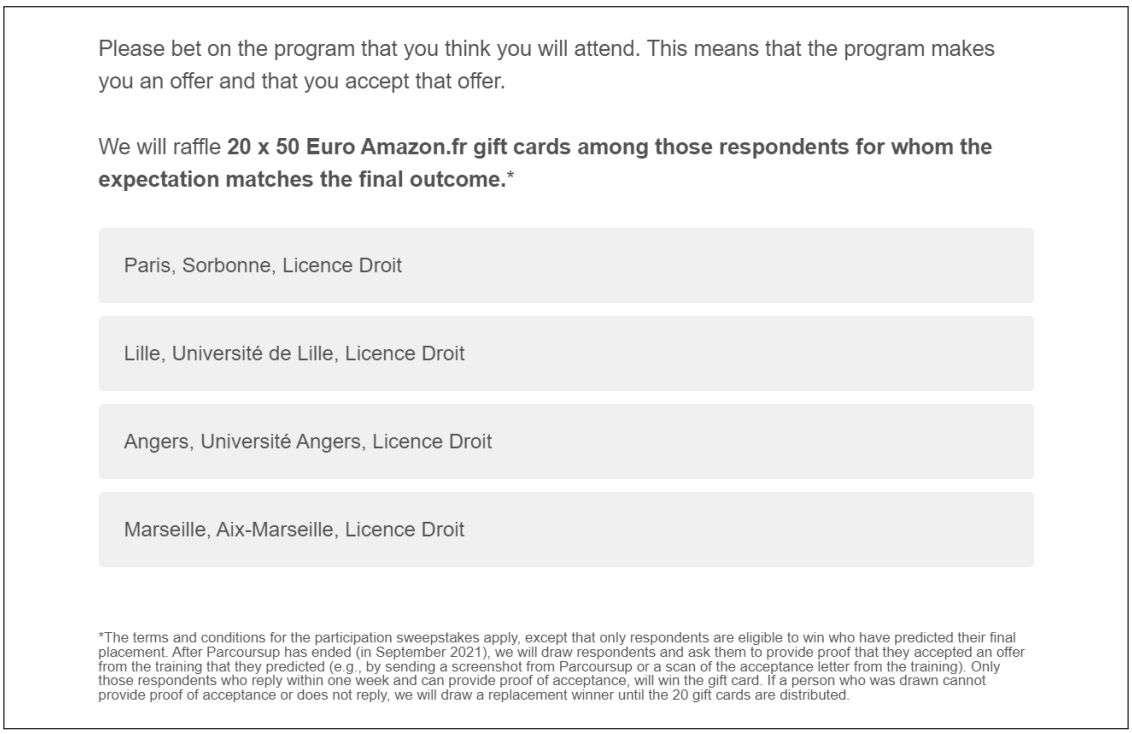
Notes: Subjects were incentivized to choose the correct statement.

Figure G.16: Screenshot of mechanism knowledge feedback



Notes: In this example, the subject had chosen the wrong answer.

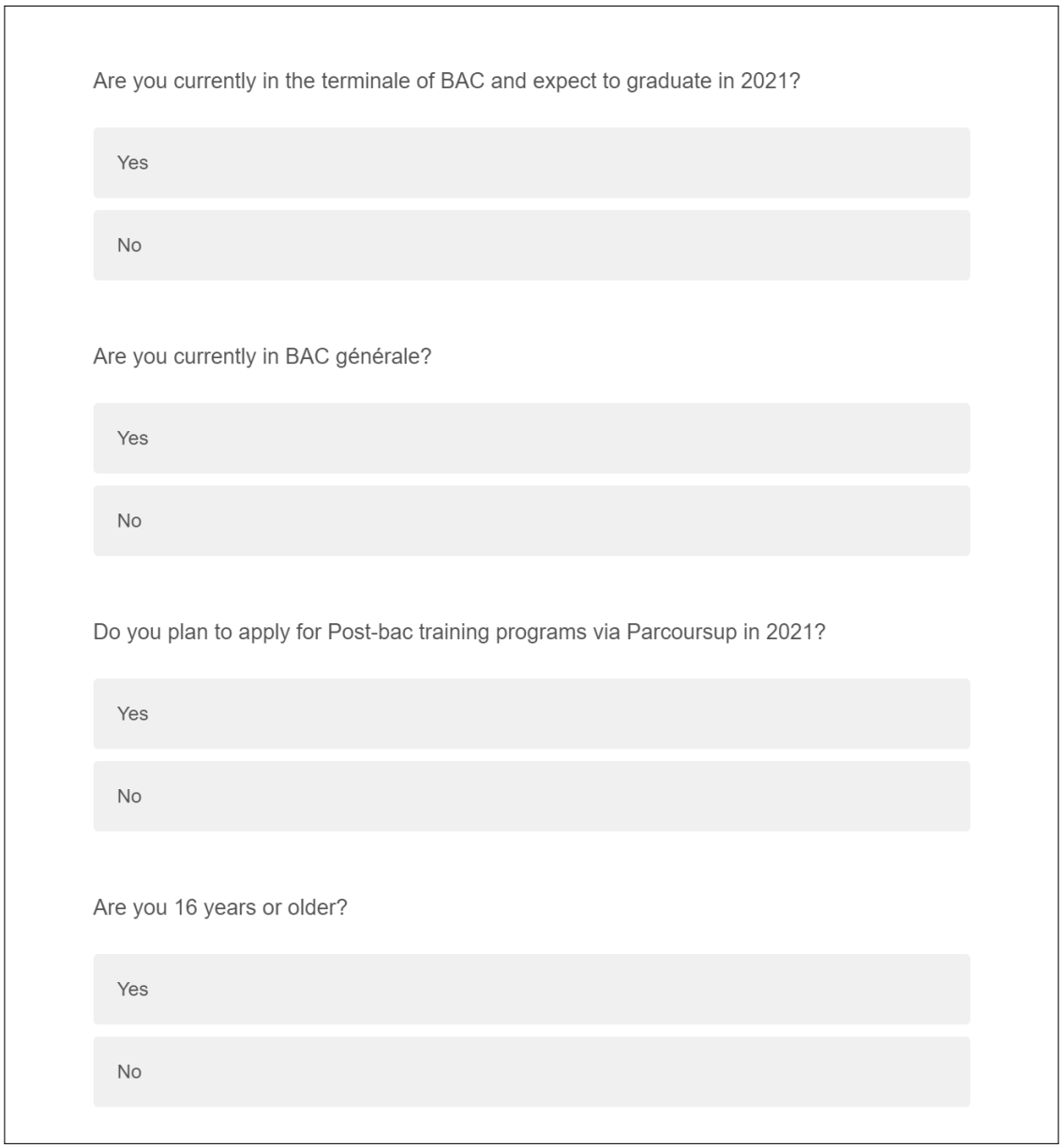
Figure G.17: Screenshot of bet on outcome



Notes: Subjects were incentivized to bet on the program they expected to attend.

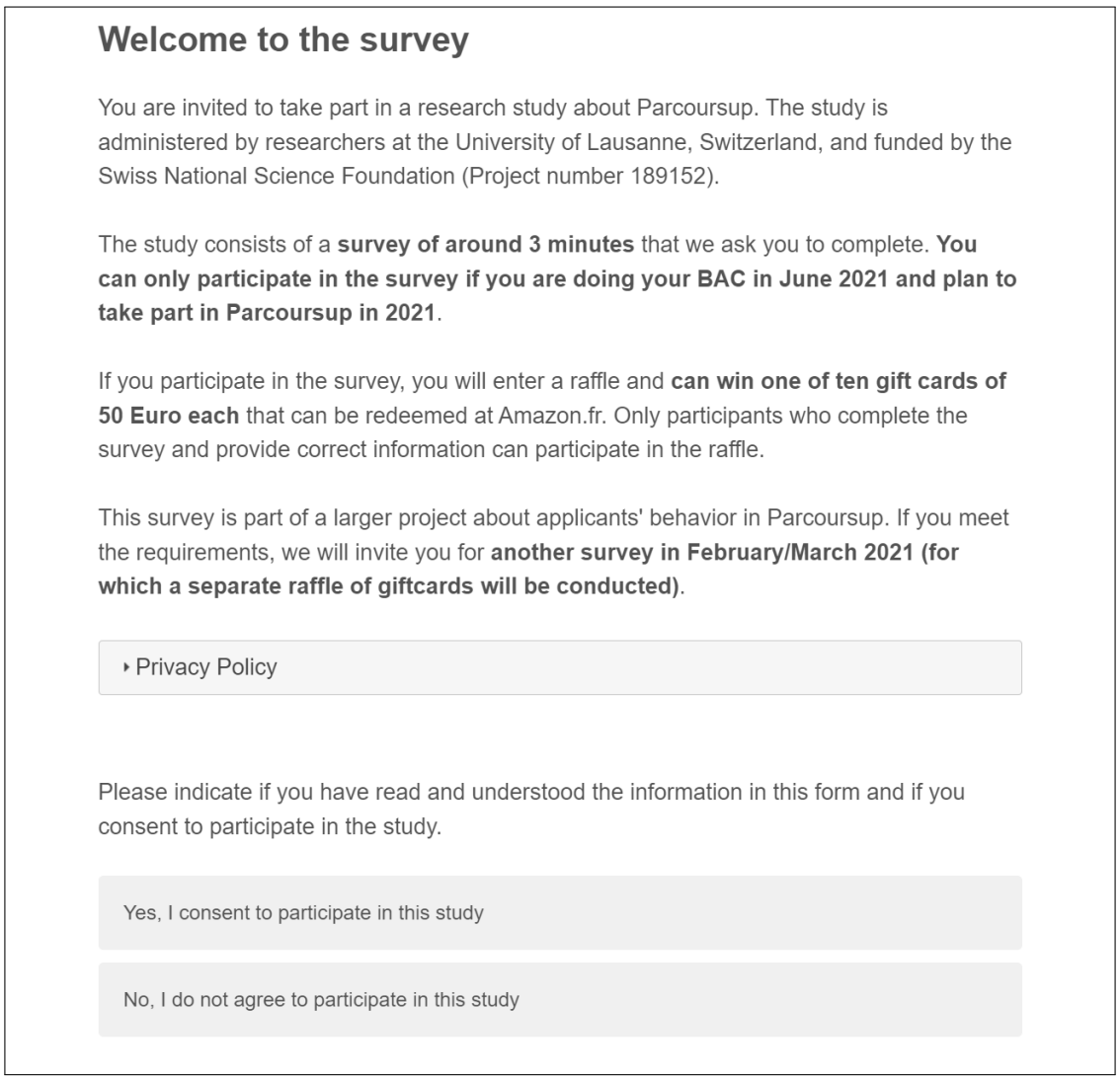
H Pre-survey Instructions (translated from French)

Figure H.1: Screenshot of pre-screening questions



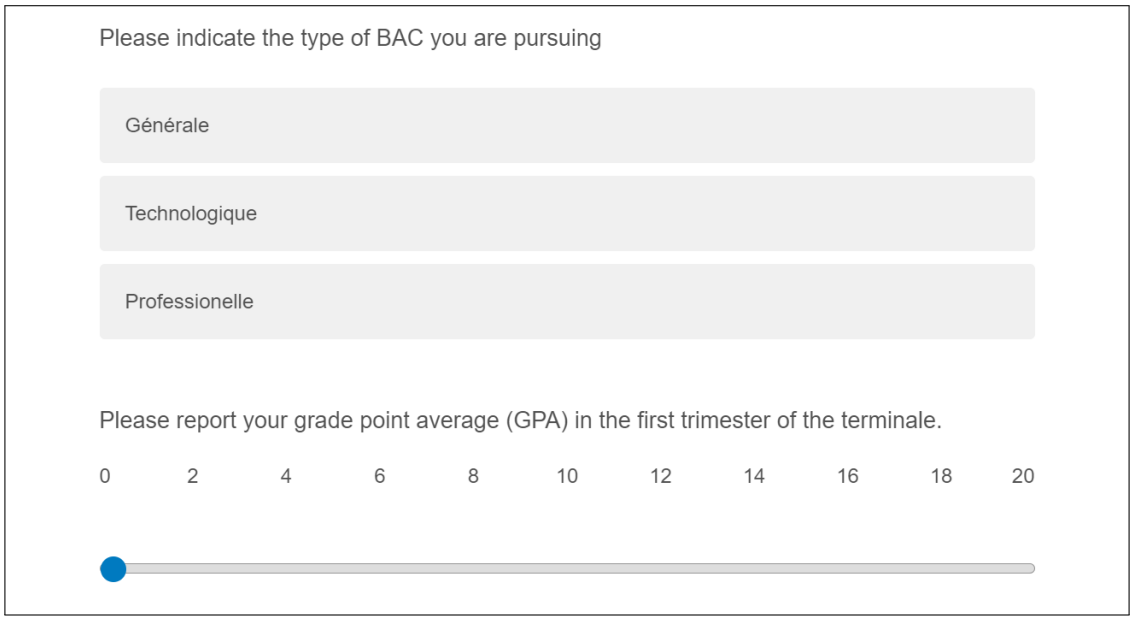
Notes: Subjects were pre-screened as to whether they belonged to the target group. The survey only continued if they answered yes to all questions.

Figure H.2: Screenshot of welcome screen and consent form



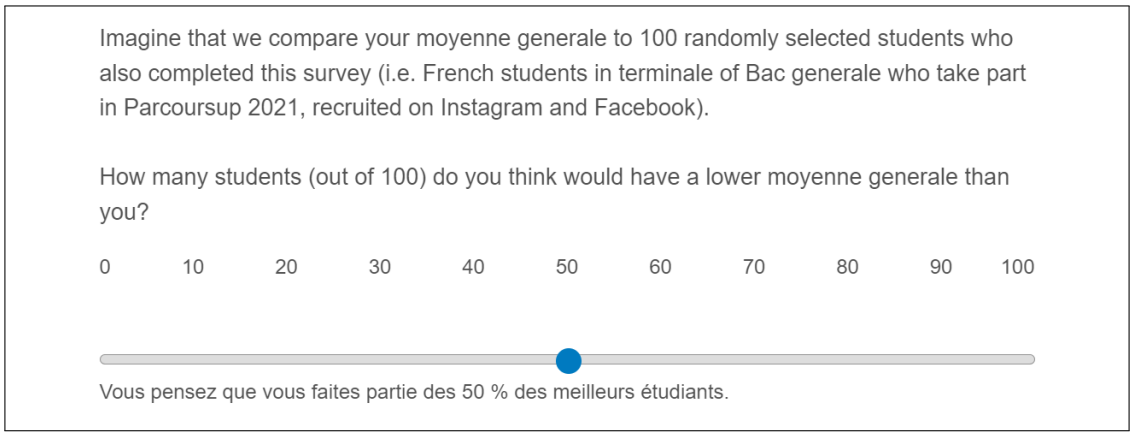
Notes: Subjects are welcomed and asked to consent to the privacy policy. The privacy policy informed participants that their responses would be matched to administrative data and pseudonymized afterwards. On the next screen, they were asked for their demographic details, similar to Figure G.2 below (omitted here).

Figure H.3: Screenshot of question on *bac* type and GPA



Notes: Subjects were asked for their *bac* type and their GPA in the previous trimester.

Figure H.4: Screenshot of question on guessed rank in the GPA distribution



Notes: Subjects were asked to guess their rank in the GPA distribution (only hypothetically).