Confidence and College Applications: Evidence from a Randomized Intervention

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Confidence and College Applications: Evidence from a Randomized Intervention*

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Abstract

This paper investigates the role played by self-confidence in college applications. Using incentivized experiments, we measure the self-confidence of more than 2,000 students applying to colleges in France. The best female students and students from low socioeconomic status (low-SES) significantly underestimate their rank in the grade distribution compared to male and high-SES students. By matching our survey data with administrative data on real college applications and admissions, we show that miscalibrated confidence affects college choice controlling for grades. We then estimate the impact of a randomized intervention that corrects students' under- and overconfidence by informing them of their real rank in the grade distribution. The intervention fully offsets the impact of under- and overconfidence for college applications. Providing feedback also makes the best students, who were initially underconfident, apply to more ambitious programs with stronger effects for female and low-SES students. Among top students, our intervention closes 72% of the gender gap in admissions to elite programs, and 95% of the social gap. We conclude that confidence is an important behavioral consideration for the design of college admission markets.

JEL-codes: I24, J24, D91, C90
Keywords: college choice, confidence, information treatment, matching mechanism, gender and social gap, survey experiment

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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., 2017; Hoxby and Avery, 2012). Gender also plays a key role. Females disproportionately enter less selective colleges and lower-paying jobs than men (Saygin, 2016; Blau and Kahn, 2017). A number of reasons have been documented for this unequal access to college, from financial constraints (Angrist et al., 2022; Bettinger et al., 2019; Dynarski, 2000; Scott-Clayton and Schudde, 2020) to preferences regarding programs or peers (Wiswall and Zafar, 2015, 2018; Patnaik et al., 2021), or information frictions (Bettinger et al., 2012; Hoxby and Turner, 2015; Bergman et al., 2019; Guyon and Huillery, 2020). There is growing interest in behavioral constraints to equal college access, with papers analyzing the role played by complexity and uncertainty in the admissions and 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 constraint to college access, namely students' over- and underconfidence regarding their academic ability, two phenomena we refer to as "misconfidence." We define misconfidence 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., 2020a; Guyon and Huillery, 2020), there is a lack of causal evidence on the impact of misconfidence on college selection.

To address this question, we combine survey and administrative data on college applications and admissions with a randomized intervention to answer the following questions: First, how large are confidence gaps by gender and socioeconomic status (SES)? Second, how much does misconfidence correlate with college applications and admissions? Finally, is the relationship causal, that is, how effective is an intervention which provides students with feedback on their real rank in the grade distribution at mitigating the role played by

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

misconfidence in college applications, and does this intervention help close the gender and social college admission gap?

Studying how confidence affects college choice is a first-order question from both an efficiency and an equity perspective. From an efficiency perspective, over- and underconfidence can be costly. Underconfident students might shy away from the most prestigious colleges, wrongly believing they have low admission chances. These students may realize post-match 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 preferred college among all the colleges for which they have a high-enough score.[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). The underconfidence of 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] We find that among top students who receive the highest honors, female and low-SES students are respectively 20.0 and 14.7 points less likely to apply to an elite program (called 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 these selective colleges might be especially advantageous for low-SES students (Black et al., 2023; Bleemer, 2021).

The French context is particularly well suited to study the role of confidence in college choices for four reasons. First, the vast majority (84%) of students enroll in public institutions that are free.[5] The absence of financial constraints is important when studying social

[2]The stability argument is important in countries utilizing stable matching mechanisms for centralized college admissions, but stability 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; 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 Falk et al. (2020a), Carlana et al. (2022), Black et al. (2015), Page and Scott-Clayton (2016), Hoxby and Avery (2012).

[5]In 2021/2022, a student typically paid 170 euros per year to enroll in an undergraduate course in a public university (Campus France, 2022), and the majority of the most prestigious programs (called CPGE) is free.

aspiration gaps as boosting confidence might fail to change student college choices when low-SES students are financially constrained. Second, students can apply only to a limited number of programs, which requires them to consider which programs are realistic before applying. Third, there is no centralized college entrance exam in France which partly explains student misperception of their position in the ability distribution. The absence of a centralized college entrance exam is a common setting around the world (see, e.g., Canada, Germany, Austria, Belgium, Mexico, the Netherlands, Denmark, Finland, Italy (except for some subjects), and others). Finally, the levels of social inequalities in access to college in France are very comparable to other developed countries, including the US (Bonneau and Grobon, 2022).

To investigate the link between confidence and college applications, we conduct a large-scale survey of high school seniors participating in the French college admission procedure in 2021. During the weeks that precede the national deadline for college applications, we collect information on student intended application lists and student perceived admission chances in each program.[6] We also use the survey to measure students' confidence in their academic ability. To do so, we ask students about their grade point average (GPA)—a score that French students find on their school report card—and what they think the rank of their GPA is 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. We incentivize belief elicitation by rewarding students who correctly guess their rank. Finally, we match our survey data with administrative data on the universe of college applicants, which contains information on student application lists, the offers they receive, and the program they ultimately enroll 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 8.5 ranks lower in the distribution than the best males. High-achieving low-SES students are also more underconfident. Their guessed rank is 4.7 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.

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

[7]The curriculum is standardized in France, which makes GPA particularly comparable across schools.

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 by 3.3 percentage points the probability of applying to one of the elite French programs (CPGE) and by 1.6 points the probability of enrolling in one.[8] Given the large gender and social confidence 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. Correcting misconfidence might also move the allocation closer to stability.

In the second part of the paper, we therefore evaluate the effect of an intervention that makes students aware of their under- or overconfidence and corrects it. We embed the intervention in our survey and randomize access to measure its causal effect. After measuring student confidence, we randomly split the survey participants into a treated group that receives feedback on their real rank in the grade distribution and a control group that receives no feedback. This intervention has two purposes: (1) to understand whether correcting misconfidence reduces its relevance for college choice, and (2) to explore whether correcting misconfidence is an effective way of alleviating the gender and social gaps.

Our results reveal that correcting misconfidence significantly reduces its importance for college choice. Providing feedback on rank reduces the role played by misconfidence in the prestige of the top-ranked program (-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. Our results show that misconfidence has a clear and 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 aspiration gap among high-achieving students. 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

[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.

male students exhibit less misconfidence than their female counterparts. 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 73% of the admission gap in elite programs. 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; it completely closes the gap in applications and admissions to an elite program (CPGE). These results show that misconfidence is a substantial behavioral constraint for equal access to college.

In the last section, we investigate 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, which makes it particularly important to understand where these misperceptions come from (Agarwal and Somaini, 2018; Kapor et al., 2020; Tincani et al., 2022; Larroucau et al., 2021; Arteaga et al., 2022). We use information on student-guessed admission chances from our survey to show two main results. First, higher confidence is associated with higher perceived admission chances in prestigious programs. Second, in the survey, 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. We show that our intervention makes misconfidence less relevant when students predict the prestige of their final match.

Our results are of direct policy interest. Concerns regarding unequal access to college have given rise to a wide range of policies to boost college enrollment among low-SES students. These policies include preferential admissions such as quotas and reserved seats (Black et al., 2023; Tincani et al., 2022; Bleemer, 2021; Otero et al., 2021; Dur et al., 2018), the provision of information about the cost and returns of colleges (Bettinger et al., 2012; Hoxby and Turner, 2013; Bergman et al., 2019; Jensen, 2010), and financial aid (Angrist et al., 2022).[9] We add a new intervention to the policymaker's toolbox that targets a behavioral constraint (rather than financial or informational) to college access, and that effectively alleviates gender and social aspiration gaps in a way that is low cost, easy to implement, and easy to scale.

Our findings can also guide policy makers in the design of college admissions systems. In some countries, students apply to colleges *before* knowing their exam scores while in other countries, students apply *after*. Our results suggest that the latter, by informing

[9]In France, concerns over self-censorship in college applications led to a major reform of college admissions in 2018, whose effectiveness in terms of social diversity is unclear (Cour des Comptes, 2020).

students on their position in the distribution, reduces gender and social aspiration gaps. Our intervention is also related to recent initiatives that give students individual feedback on their admission chances in schools (Arteaga et al., 2022; Larroucau et al., 2021). Both interventions are relevant in different contexts. While personalized information on admission chances is the most precise way of informing students, calculating these probabilities is often not possible without rich data on student rank, program competitiveness, and admission criteria. This is typically the case in countries in which the admission criteria are fuzzy or in which there is no centralized college entrance exam, like in France, England, Canada, Mexico, South Korea, and others.[10]

Our paper contributes to a literature showing the relevance of overconfidence in a myriad 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 individuals' ideological extremism, partisan identification, and voter turnout (Ortoleva and Snowberg, 2015). Overconfidence matters because it can persist, even in settings with repeated feedback (Huffman et al., 2022). 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, such as Dargnies et al. (2019) for the effect of confidence on early job market offers and Barron and Gravert (2022) and Bruhin et al. (2022) for its effect on effort provision. Our study adds to this literature by shedding light on the causal effect of confidence in a high-stakes real world environment.

Our paper aligns with a vast empirical literature that shows gender and social gaps in confidence and aspirations both 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; Landaud et al., 2019; Sterling et al., 2020; Cortés et al., forthcoming). A handful of recent papers bring indirect evidence on how confidence gaps impact education and career choices. Carlana et al. (2022) and Falk et al. (2020b) demonstrate that mentoring programs, offered to immigrants and low-SES students, affect both their confidence and educational choices. In the French context, Guyon and Huillery (2020) observe that low-SES middle-school students underestimate their relative academic potential which correlates with their choice of an academic high school track. In comparison to these studies, we experimentally modify

[10]In France, college admission criteria and their weights are not transparent. Policymakers are not able to calculate personalized admission chances. Students typically use their GPA as a proxy for their admission chances.

students' academic confidence, enabling us to quantify the causal effect of confidence on education choice.

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). While the design of matching markets has traditionally been theory-driven, 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 done to uncover the role played by bounded rationality and participant inexperience (Li, 2017; Pycia and Troyan, forthcoming; Bó and Hakimov, forthcoming; Gonczarowski et al., 2022), individuals' expectation-based loss aversion and rank-dependent utility (Dreyfuss et al., 2022b; Meisner and von Wangenheim, 2023a; Meisner, 2023; Dreyfuss et al., 2022a; Chen et 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.[11] 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 that studies the effect of ability feedback on student achievement. Using field experiments, several papers document the effect that knowledge of students' 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 directly complements this literature by exploiting information not only on the feedback that students receive on their rank, but also on their initial (often incorrect) perception of their rank, and to shed light on the relationship between both.

In a different setting, Bobba et al. (2023) analyze the role played by student perceived ability on their high school choice. After asking Mexican middle school students to take a mock exam, the authors provide individualized performance feedback to a random sample of ninth-graders, which leads high-achieving students to increase applications to academic tracks, and low-achieving students to reduce them. Although related in topic, our papers

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

[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).

complement each other in several ways. We largely focus on gender differences in confidence and aspirations. We also adopt different approaches to analyze social gaps. While we bring reduced-form evidence on the effect of rank feedback on both high-SES and low-SES students, Bobba et al. (2023) estimate treatment effects on relatively disadvantaged students and rely on a structural model to extrapolate the results to a more diverse population of students. Finally, we analyze college choice, as opposed to high school choice in Bobba et al. (2023). As a high-stake and high-choice environment, college choice is particularly prone to self-censorship from students, and therefore to gender and social inequalities in aspirations that can have large long-term effects on labor market inequalities.[13]

Also related, Tincani et al. (2022) analyze the effect of a preferential college admission program in Chile that gives students in the top 15th percentile of their school GPA automatic college admission. The policy increased college enrolment by 32%, but the treatment effect was significantly lower for students who, despite being at the school admission cutoff, perceived themselves as being below the cutoff.[14] Using a structural model, the authors quantify the role played by student biased beliefs on the overall effect of the preferential college admission program. The main difference of our paper is methodological: whereas Tincani et al. (2022) use simulations from a structural model, we study how misconfidence affects college enrolment using a randomized intervention. Interestingly, both approaches yield similar conclusions.

Finally, we contribute to a blooming literature documenting students' incorrect beliefs in their admission chances and the ensuing costs (Agarwal and Somaini, 2018; Kapor et al., 2020; Larroucau et al., 2021; Arteaga et al., 2022). What drives these incorrect beliefs is less clear. We show that student under- and overconfidence in their academic ability are important determinants of their incorrect beliefs.

The paper is organized as follows. In Section 2, we describe the institutional context and provide descriptive evidence of aspiration 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

[13]Other differences exist between the two papers. Compared to Bobba et al. (2023), we provide feedback on relative performance rather than absolute performance, and we use incentivized measures of confidence. On the other hand, Bobba et al. (2023) nicely show what the equilibrium effect of scaling up an information intervention would be, using a school choice model.

[14]This lower treatment effect is likely due to student overpessimism reducing their chances of taking the college entrance exam, a necessary step for admission.

choice. Section 6 presents the results of the experimental intervention, and Section 7 looks into potential mechanisms. Finally, in Section 8, we conclude.

2 Institutional Setting

2.1 College Admission in France

Higher education in France. In France, education is compulsory for children between the ages of three and 15 and consists of three cycles: primary school up to age 11, middle school (*collège*) between ages 11 and 15, and high school (*lycée*) from 15 to 18. At the end of high school, students can obtain the high school diploma (called *baccalaureat*), which allows them to enter higher education. Three types of high schools exist that lead to three different diplomas: *bac général* (preparing for university education), *bac technologique* (preparing for short-term studies), and *bac professionnel* (preparing for a vocational career). While students from the three high-school tracks can apply to any higher education program, the curriculum in the general, vocational, and technical tracks are very different, so that student aspirations and admission chances are different. It is also more difficult for students in vocational and technical tracks to compare their grades to those of general track students. Hence, in the remainder of the paper, we focus on students from the general high-school track (*bac général*), who account for 83% of the students in university programs and 93% of students in the elite track as defined below. In 2021, 421,000 *bac général* seniors 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 newly minted *bac général* graduates. These classes constitute the most prestigious educational track. They last for two years and prepare students for the competitive entrance exam of the *grandes écoles*. Preparatory classes are free for students. Importantly, if students fail to enter the elite colleges after preparatory class, they do not lose the two years, as they can enter the third year of public universities. Elite colleges, such as Écoles Normales Supérieures (ENS), Ecole Polytechnique, engineering schools, business and management schools, can be either public or private.

Most of them last for four years. In the rest of the paper, we will refer to CPGE as the *elite track*.[15]

- 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, 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 post-secondary 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, ...).[16] Using the platform, students can then submit up to 10 unordered choices, and within these choices they can make a maximum of 20 sub-choices. For example, a student can apply to a science elite track in up to 20 different institutions. This would count as one choice and 20 sub-choices.[17] We refer to a higher education institution as an *institution* (e.g., Paris Sorbonne), and we refer to a subject within an institution as a *program* (e.g., Paris Sorbonne, Math). In Figure A.1 in the appendix, we plot a histogram of the number of choices that students made in 2021. The spike at 10 choices indicates that for many students the choice limit is binding. However, there are also many students who do not exhaust the limit and many who apply to more

[15] 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.

[16] See `https://dossier.parcoursup.fr/Candidat/carte` (retrieved 11/04/2022). Each program provides the following information: public or 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.

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

than 10 programs (e.g., by using their sub-choices or applying to programs without a limit on the number of choices).

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 typically 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 had to submit their application list by March 11. Importantly, students finalize their applications before taking the centralized high school exit exam in June.[18] This means that when students submit their applications they are only aware of their average teacher-given grades (GPA).[19] More specifically, at the end of each term (a three-month period), students receive a one-page document summarizing their grades in each subject. This sheet also indicates the student's GPA and rank within their class. This is the only information that students have to judge their academic ability and credentials relative to their peers. In the absence of a unique college entrance exam that gives students accurate information on their position in the ability distribution, we expect student under- or overconfidence to have a larger effect on their college applications. In the conclusion, we discuss how the effect of our "confidence-

[18]Usually, the *bac* grade is a weighted average of continuous assessments and the centralized exit exam grades. In 2021, the exit exams were cancelled due to the Covid pandemic 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.

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

correcting" intervention might vary in a different environment, for instance, one with a college entrance exam used by all colleges to rank students.

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 their GPA as a proxy for their admission chances. The administrative data on student applications and admissions shows that this approximation is reasonably accurate as student GPA is a key determinant of their priorities. The average GPA of the students who receive offers strongly decreases over time, and this is true for all programs, as shown in Figure A.2. Programs predominantly start by making offers to students with the highest GPAs before progressively issuing offers to students with lower grades. Consistent with this finding, the French Court of Auditors also identified GPA as a dominant criterion in flagship programs using machine-learning methods on student applications and admission decisions (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 (a program in the top 10th percentile of the prestige distribution) on student GPA and a set of high school fixed effects (see Appendix C for details). Only 8.2% 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 0.084 to 0.093 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 Aspiration gaps by gender and socioeconomic status

A rich literature has documented aspiration gaps by gender and socioeconomic status (Falk et al., 2020a; 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. To measure the prestige of a program, we consider the pool of students enrolled in the program, and we define the prestige of the program as the average high school diploma grades of these students. 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 in Section 3.2.

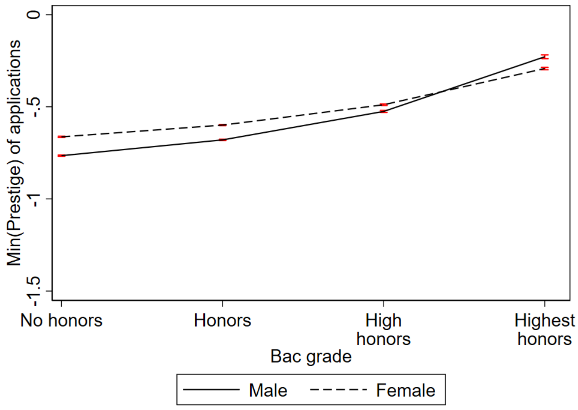
Figure 1 shows the minimum prestige of the application list (i.e., the prestige of the "safe" program) and its maximum prestige (i.e., the prestige of the "top" program) by gender and by academic achievement. The X-axis orders students from the lowest achievers who received "No honors" to the highest achievers who received the "Highest honors."[20]

Aspiration gap by gender. We find large gender differences in the prestige of the "top" programs. When building their application portfolio, the top program of high-achieving female students is significantly less prestigious than the top program of high-achieving males. This female modesty has direct consequences for their college admissions. Females with the highest honors are matched to programs with a 0.35 SD lower prestige than equally good males (see Figure A.3a in the appendix). We find only small gender differences in the prestige of the "safe" program.

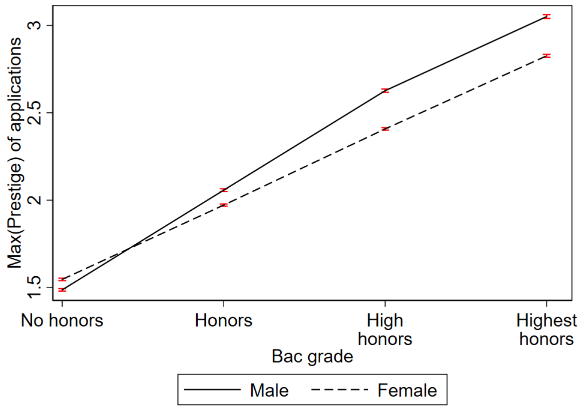
An alternative measure of aspiration is whether students apply to at least one of the prestigious elite tracks (CPGE). Figure A.4a in the appendix, shows that, among students receiving the "Highest honors," female students are 20.0 percentage points less likely to apply to an elite track and 18.5 points less likely than males to enroll in one. The large

[20]In France, high school diploma grades translate to the following 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*).

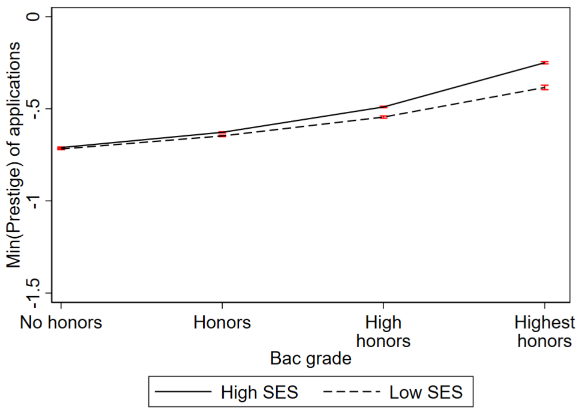
Figure 1: Prestige of applications by gender and socioeconomic status



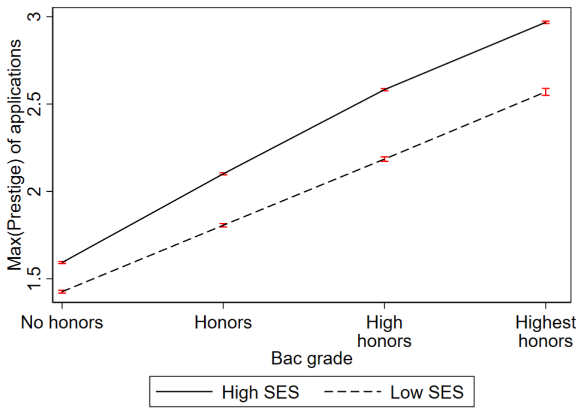
(a) Min(prestige) by gender



(b) Max(prestige) by gender



(c) Min(prestige) by SES



(d) Max(prestige) by SES

Notes: The figures show the minimum and maximum prestige of the programs in the application list by honors level and gender/SES. The prestige of a program is defined as the mean honors level of all enrolled students. Bars indicate 95% confidence intervals.

gender aspiration gap we document in France is consistent with evidence in other countries that high-achieving females are less likely than males to select highly paid professions and more selective colleges (e.g., Boring and Brown, 2016; Delaney and Devereux, 2021a; Saygin, 2016; Reuben et al., 2019).

Aspiration gap by socioeconomic background. We also find remarkable aspiration gaps by socioeconomic background. Students from a lower SES apply to significantly less prestigious "top" programs, with the largest differences among the best students (see Figure 1d). This ambition gap has consequences for admissions. Among students with the highest honors, low-SES students are matched to programs that are 0.55 SDs less prestigious than high-SES students. We do not find large differences in the prestige of the "safe" program (see Figure 1c). We find a similar pattern in applications to the elite track (CPGE). Among students receiving the highest honors, low-SES students are 14.7 percentage points less likely to include an elite track in their application list than high-SES students (see Figure A.4c in the appendix) and they are 10.7 percentage points less likely to enroll in one. The striking social gap in the aspirations we document brings one more piece of evidence to a well-documented fact: high-achieving, low-SES students are less likely to select prestigious academic tracks than high-SES students (Falk et al., 2020a; Carlana et al., 2022; Black et al., 2015; Page and Scott-Clayton, 2016; Hoxby and Avery, 2012).

Takeaway. The large aspiration gaps by gender and social background we find are a source of concern because high-achievers are precisely those with the highest chances of attending prestigious colleges with higher returns (Zimmerman, 2019; Anelli, 2020; Altonji et al., 2016; Kirkeboen et al., 2016; Hastings et al., 2013). While there may be a variety of reasons behind the aspiration gap, the literature documents systematic confidence gaps by gender and social background (e.g., Niederle and Vesterlund, 2007; Almås et al., 2016; Guyon and Huillery, 2020). The French administrative data also suggests that differences in confidence may indeed contribute to explaining the aspiration gaps. Figure A.5 shows that, conditional on applying, high-achieving female and low-SES students are significantly more likely to receive an offer from their top program. Receiving an offer from the most prestigious program applied to can be seen as an indicator of an under-ambitious application list, suggesting underconfidence. While suggestive, this evidence is indirect. In the following sections, we combine survey and administrative data to explicitly identify the role of self-confidence in explaining the aspiration gap.

3 Data and intervention

3.1 Survey data

Social media recruitment. We conducted a large-scale survey of students participating in the French college admission procedure 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] Therefore, we recruited our sample using social media ads on Instagram, Snapchat, and Facebook; an effective recruitment channel as the overwhelming 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. Moreover, 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 provides additional details on 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 et al., 2020; Jäger, 2022), in particular when stratifying based on demographics, as we do in this paper.

In our setting, Table A.1 also 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 iden-

[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 according to a survey by Diplomeo (Leroux, 2020).

tical 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 provides the instructions. We started by collecting demographic information on student birth date, gender, postal code, and school name. We employed these variables to match our survey data to the administrative data for students who did not provide their national student identifier (INE). Moreover, we elicited student risk preferences by asking them about their general willingness to take risk on an 11-point scale (Dohmen et al., 2011).

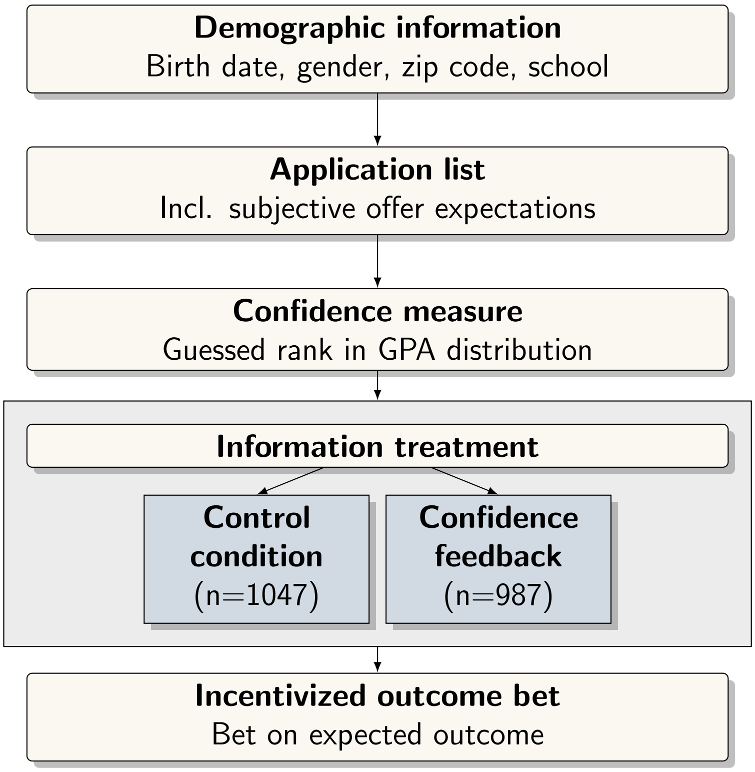
Student intended applications. We then asked students for the list of programs they were planning to apply to on Parcoursup. Students could enter between two and ten programs. For each program, we asked them to type in the city, the institution, and the program name. Finally, for each program on their 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 is the most salient

[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, the French academic year is divided into three academic terms that last three months each (Sept-Nov, Dec-Feb, and March-June). At the end of each term, students receive a one-page document summarizing their average grades in each subject, and their average grades across all

Figure 2: Survey Design



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

subjects. We asked students to report the latter grade. When participating in our survey they had not yet received the second-term GPA, so we asked them for the first-term GPA. Figure A.7 shows that their 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] Note that 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.

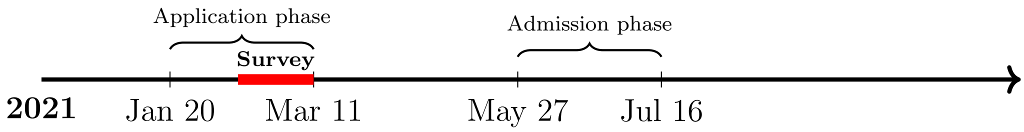


Figure 3: Survey timing in the college admissions process

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 on the GPA of French students was not available yet.[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 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). We show, when presenting the information treatment, that the grade distribution of students in the pre-survey and in the administrative data are similar, especially for high-achieving students.

[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.

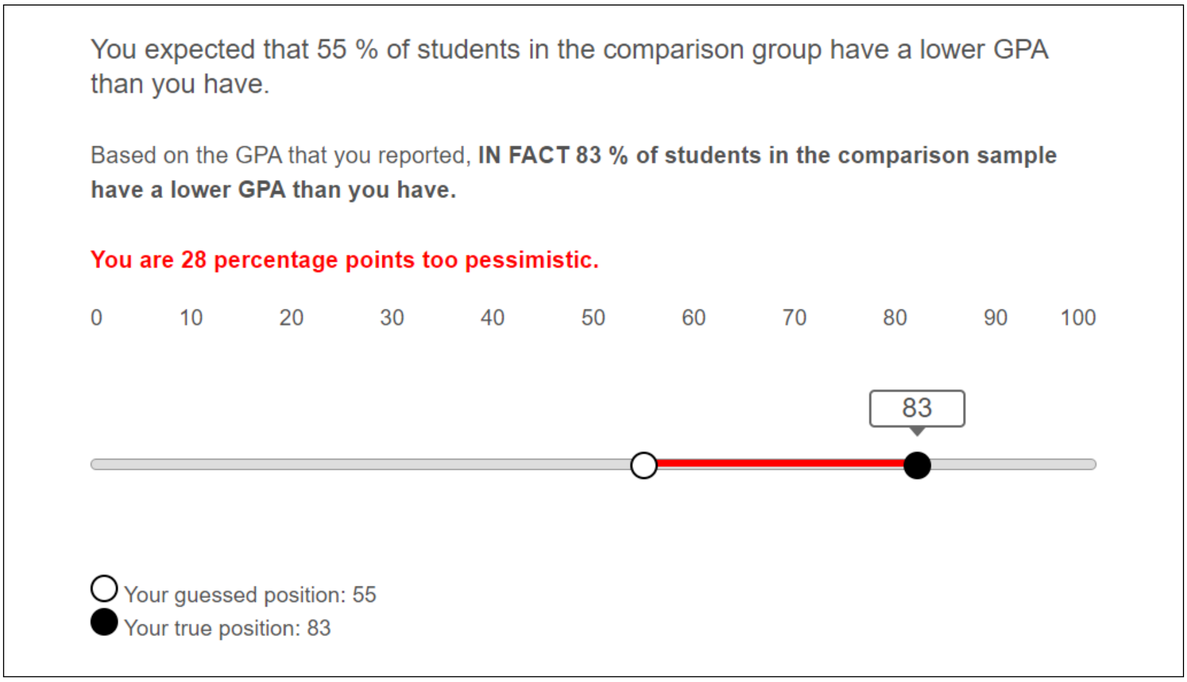
Information treatment: Correcting over- and underconfidence. The second part of the survey aims at measuring the causal effect of student confidence on their college choices. Shedding light on this relationship requires dealing with the endogeneity of a student's confidence which might be correlated with many unobserved traits. To address this endogeneity, 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 feedback. The feedback provided is simple, as illustrated in Figure 4. On a slider, we show students both their guessed rank and their real rank. The gap between the guessed and the real rank illustrates the degree of their misperception.[29] 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. However, Figure A.8 shows that the rank information we would have provided using the national distribution would have been similar. We will systematically report results using both distributions in the paper.

In addition, to make large misperceptions of one's rank more salient (i.e., strong over- and underconfidence), we highlighted the distance between the guessed rank and the real rank in three different colors depending on how large the mistake was. When a student's guess was within three ranks of the real rank, we colored the gap green to show a small over- and underconfidence (see Figure G.12 in the appendix). When a student's guess was between three and ten ranks away from the real rank, we colored the gap yellow to stress a medium over- and underconfidence (see Figure G.13). Finally, when a student's guess was more than ten ranks away from the real rank, we colored the gap red to highlight a large over- and underconfidence (see Figure 4). Correspondingly, the feedback stated: "You are X ranks too optimistic/pessimistic" in green, yellow, or red font.

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 the final applications submitted by the students. To capture short-term outcomes, in the very last part of the survey (i.e., after the information treatment), we

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

Figure 4: Screenshot of grade feedback



Notes: After subjects 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.

asked 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.[30]

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, 2022). The data contains information on student demographic characteristics, such as gender, age, parent profession, high school, and the final high school

[30] We rewarded students after the end of the allocation 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.

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.[31]

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.7 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).[32] Manual workers, low-skilled employees (working and retired), and the unemployed are considered to have low socioeconomic status. We classify a student as having a low SES if both of the student's parents are low SES (or if one is low SES and the other parent is missing). Otherwise, we classify the student as having 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. We standardize grades 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

[31]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.

[32]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).

meaningfully change the prestige of programs.[33,34] Figure A.6 in the appendix shows the distribution of the resulting prestige index.

Let us justify why, to characterize an aspiration gap, we use the prestige of applications to indicate aspirations. Instead of prestige, other program characteristics, like college access rate, could be used to document an aspiration gap. However, college 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 selective programs 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. To illustrate this point, Appendix B reports the list of the 15 most prestigious programs and the 15 most over-demanded programs, and shows correlations between the prestige and access rate.

4 Evidence on confidence gaps

4.1 Confidence gaps by gender and SES

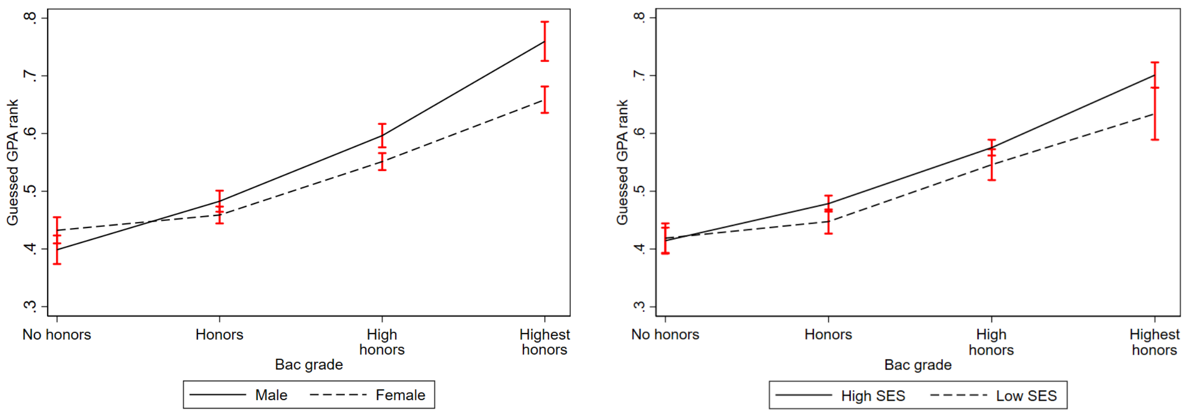
Gender confidence gap. We start by presenting descriptive evidence on students' confidence in their relative ability. Figure 5 plots individuals' beliefs about their rank in the GPA distribution (Y-axis) as a function of their high school diploma grade (x-axis). The higher the rank on the Y-axis, the higher they believe they are in the GPA distribution.

Figure 5 shows 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.9 in the appendix 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

[33] Alternatively, we could use the 2020 data, which yields prestige scores that are highly correlated with those based on 2021 data, among the programs the survey participants apply to (r=0.930). However, it has the downside that for more than 12% of the programs from 2021 no prestige score can be calculated because these programs were not available in 2020. As our main results are very similar irrespective of calculating prestige based on 2020 or 2021 data, we decide for the latter.

[34] Similarly, MacLeod et al. (2017) calculate the mean admission scores of graduates to measure a program's reputation in Colombia. They find that the reputation increases graduates' earnings and earnings growth.

Figure 5: Guessed GPA rank by honors and gender/SES



(a) Guessed rank by gender

(b) Guessed rank by SES

Notes: The figures show the average guessed GPA rank by actual honors. Bars indicate 95% confidence intervals.

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.[35]

To quantify the confidence gap, we construct the variable Misconfidence:

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

Misconfidence$_i$ corresponds to the difference between student i's guessed ability rank and their real rank. 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. While the original values of this variable range from -100 to +100, we rescale the variable to range between -1 to 1.

[35] Note that the underconfidence by students at the top and the overconfidence by students 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, for mechanical reasons, misconfidence is negatively correlated with true ability. To control for this mechanical effect in a flexible way, in what follows we include the real rank variable in all regressions and control for honors fixed effects.

The larger this variable, the more overconfident (and the less underconfident) a student is. We plot the distribution of misconfidence in Figure A.10.

Moreover, to see 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 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.

We then regress the variable misconfidence on a female dummy variable, controlling for student real rank at the national level (from the administrative data). The results, reported in Table 1, show that female students are 1.8 percentage points less confident than male students on average—i.e., conditional on real rank, they perceive themselves as 1.8 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 8.5 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.

Our findings contribute to the long-standing literature suggesting that men are, on average, more confident regarding their ability than women, partly explaining gender differences in the willingness to compete (Bandiera et al., 2021; Niederle and Vesterlund, 2007; van Veldhuizen, 2022; Gillen et al., 2019). Our finding that the gender confidence gap is driven by top-performing students is consistent with Buser et al. (2022). They find that gender differences in the willingness to compete among Swiss students are substantially stronger for high-ability students compared to low-ability students.

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 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.9b in the appendix, in which we plot students' guessed GPA rank (y-axis) against their real rank (x-axis). Panel B of Table 1 quantifies these confidence gaps. Low-SES students are, on average, 1.8 percentage points less confident, which is mostly driven by underconfident

Table 1: Confidence gaps by gender and SES

	Misconfidence	Underconfidence	Overconfidence
Panel A: Female coefficient			
Total	-0.018**	0.036***	0.019*
	(0.007)	(0.008)	(0.010)
	[2034]	[1147]	[857]
No honors	0.039**	0.001	0.044**
	(0.017)	(0.019)	(0.017)
	[473]	[70]	[397]
Honors	-0.020*	0.013	-0.003
	(0.012)	(0.012)	(0.013)
	[690]	[316]	[363]
High honors	-0.037***	0.037***	0.018
	(0.012)	(0.012)	(0.012)
	[552]	[448]	[91]
Highest honors	-0.085***	0.077***	-0.008
	(0.019)	(0.019)	(0.062)
	[319]	[313]	[6]
Panel A: Low SES coefficient			
Total	-0.018**	0.033***	0.014
	(0.008)	(0.009)	(0.011)
	[2000]	[1128]	[842]
No honors	0.008	-0.001	0.011
	(0.017)	(0.019)	(0.017)
	[462]	[70]	[386]
Honors	-0.024*	0.028**	0.018
	(0.013)	(0.012)	(0.014)
	[680]	[310]	[359]
High honors	-0.029**	0.032**	-0.013
	(0.014)	(0.015)	(0.014)
	[544]	[440]	[91]
Highest honors	-0.047*	0.052**	0.101
	(0.024)	(0.023)	(0.083)
	[314]	[308]	[6]
True rank (admin)	✓	✓	✓

Notes: The table reports the OLS coefficients from regressing the misconfidence variable (guessed rank minus the real rank), the underconfidence variable (negative misconfidence if underconfident), and the overconfidence variable (misconfidence if overconfident) on a female indicator (in Panel A) and a low SES indicator (in Panel B), while controlling for real rank. Confidence measures are defined based on the national level GPA distribution. The regressions are conducted on the total sample and split by honors categories. Robust standard errors are in round parentheses and the number of observations in square brackets. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

students. Once more, the confidence gap is much larger among high-achieving students. For students with the highest honors, low-SES students are 4.7 percentage points less confident than high-SES students, with most of this difference being driven by underconfident students.

Our findings complement a body of evidence showing that low socio-economic status students are less accurate in assessing their abilities (Falk et al., 2020b). In France, Guyon and Huillery (2020) had previously found that low-SES high school students score 0.15 SDs lower on a "scholastic self-esteem" index (including items like "being just as smart as others"), despite having the same high school grades. In Mexican middle schools, Bobba et al. (2023) find that high-achieving, low-SES students update their ability beliefs less in response to positive feedback compared to high-SES students.

5 Misconfidence and college choice

Our results so far document a large confidence gap between female and male students and between students from low and high social backgrounds. The question we address in this section is: How much do under- and overconfidence affect student college applications and admissions?

Outcomes. First, we test whether misconfidence is associated with the prestige of the application lists. Among all applications submitted by a student, we compute (i) the minimum prestige of 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 track (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 track.

Estimation strategy. To estimate whether overconfidence predicts application behavior and outcomes, we use the following specification:

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

Y_i are the outcome variables just described (prestige of applications and match as well as dummy variables for applying and being matched to a CPGE). The variable 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 influence of misconfidence, keeping the real rank constant. We include indicators of a student's honors to control for academic ability more flexibly.[36] Moreover, we control for risk preferences (Dohmen et al., 2011).[37] We only consider students in the control group to ensure that the outcome variables are unaffected by the information treatment.

Results Table 2 shows to what extent student misconfidence is associated with applications and admissions. If student confidence did not matter for college choice, that is, if students only applied based on their academic ability, then student real rank and honors fixed effects would be the only variables affecting applications, and the misconfidence variable would have no effect. This is not what we observe.

Panel A shows that, holding ability constant, misconfidence strongly correlates with application behavior. More confident applicants 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 track (CPGE).[38] 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 with the prestige of the "safe" program (see Min Prestige). This suggests that students who overestimate their overall admission chances are not more likely to skip safe options that are within reach. We then show a similar positive association between confidence on

[36] As the impact of actual 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.

[37] We control for risk preferences because some students might perceive an application to a CPGE as risky. CPGEs are two-year programs that prepare students for the competitive exam to enter one of the Grande Ecole. When students fail all exams, they can directly enter the third year of university. they do not lose two years. Although the existence of these bridges is relatively well known, some students might not be aware of it. They would then perceive a CPGE as a risky choice.

[38] 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.

Table 2: Association between misconfidence and college applications and admissions

	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
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: 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 her rank at the national level, using the GPA distribution from the administrative data. See Table A.4 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. In Column (1), the dependent variable is the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list, in Column (2), minimum prestige of the application list, in Column (3) the average prestige of the application list, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. The sample includes students from the control group and students from *bac général*. Robust standard errors are reported in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

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.

Finally, we investigate whether the relationship between confidence and college applications is driven more by underconfident or by overconfident students. In Panel B of Table 2, we replace the misconfidence variable with the underconfidence and overconfidence variables. We find that both underconfidence and overconfidence correlate with the prestige of the program selected by students. Underconfidence affects the likelihood of applying to an elite track 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 asymmetric effect of under- and overconfidence on applications to the elite track directly translates into the same asymmetry in terms of admission chances. Underconfidence is associated with 2.5 points lower admission chances to CPGE, while overconfidence is not associated with CPGE admission chances. In Panel A of A.4, we show that the results are very similar when we use the GPA distribution from the pre-survey sample to define a student real 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 application behavior is causal.

6 Effect of correcting misconfidence on college choice

6.1 Misconfidence no longer matters after feedback

Estimation strategy. In this section, we study whether correcting students' misconfidence by providing feedback on their real rank in the ability distribution has a causal effect on their application behavior.[39] To measure the effect of correcting misconfidence, we ran-

[39] 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'

domly 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 the highest honor students, 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:

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

Y_i is the outcome. Feedback$_i$ is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability distribution. Feedback$_i$ is equal to zero for students in the control group. As defined above, Misconfidence$_i$ 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 refer to these students as having "well-calibrated" beliefs. All regressions control for a student's real rank. β_1 measures how much misconfidence affects college choice for students who do not receive feedback. This coefficient indicates whether, conditional on real rank, over- and underconfidence are relevant for college choice, replicating our analysis from Section 5. The coefficient β_2 measures how much providing feedback affects the relevance of misconfidence on application behavior. Moreover, β_3 estimates the effect of providing feedback for students who are neither overconfident nor underconfident as they correctly guessed their rank. Finally, X_i includes honors fixed effects to control for ability differences more flexibly, as well as controls for risk preferences. Finally, when informing students on their rank, we

strategies within the matching mechanism. 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 (see Appendix B for an explanation why the prestige measure is better suited). Also, in the interest of space, we skip some pre-registered outcomes in the main text and report them in Appendix F.

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.[40]

Effect of feedback. Table 3 reports the effect of providing feedback on the students' application list (in columns 1 to 4) and on their final match (in columns 5 and 6). The first 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, unsurprisingly, correcting misconfidence 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. The treatment effect is large. Without feedback, a student whose misconfidence is 10 percentiles higher applies to a top program that is 0.06 SDs more prestigious. Providing feedback reduces this boosting effect by 0.05 SDs, to the point that it makes misconfidence 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 track (CPGE).[41] Table A.4 in the appendix shows to what extent misconfidence predicts college applications, separately for students who are in the control and treatment group. The coefficients in Panel B (treatment group) show that student misconfidence is no longer associated with college choice once we provide feedback to students. This conclusion carries over to all the other outcomes we consider.

We check next whether correcting student misconfidence has the same effect for students who are initially underconfident and those who are initially overconfident. Three questions motivate the investigation of these heterogeneous treatment effects. First, we want to understand whether informing students on 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 panel B of Table A.5 show that,

[40] In Table A.6, we use the reference sample from the administrative data instead and find equivalent results to Table 3.

[41] Interestingly, the treatment seems to close 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 ($p = 0.168$).

Table 3: Effect of correcting misconfidence on college applications and admissions

	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
Misconfidence	0.613***	0.101	0.423***	0.272***	0.426***	0.147***
	(0.167)	(0.080)	(0.117)	(0.065)	(0.160)	(0.046)
Rank feedback	0.052	0.007	0.037	-0.010	0.002	0.025
	(0.044)	(0.024)	(0.034)	(0.019)	(0.045)	(0.015)
Rank feedback × Misconfidence	-0.491***	-0.024	-0.258**	-0.105	-0.104	-0.107**
	(0.179)	(0.085)	(0.127)	(0.069)	(0.176)	(0.054)
Constant	1.399***	-0.812***	0.078	-0.056**	-0.544***	-0.065***
	(0.076)	(0.035)	(0.049)	(0.025)	(0.064)	(0.018)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.226	0.119	0.335	0.198	0.464	0.102
Observations	2034	2034	2034	2034	1793	1793
Mean outcome	2.292	-0.521	0.874	0.260	0.691	0.098

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 prestige (in terms of average grades of admitted students) of the application list, in Column (2), minimum prestige of the application list, in Column (3) the average prestige of the application list, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the outcome is the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. Only students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1, ^{**} < .05, ^{***} < .01$.

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 include some programs that are unattainable in their application. No longer applying to these programs leaves the prestige of the final match unchanged.

Second, does informing students on their underconfidence make them revise their applications towards more prestigious programs, potentially at the cost of no longer including 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 influence of misconfidence on the prestige of student safe choice. Correcting underconfidence does not come at the cost of reduced applications to safe programs.

Finally, when it comes to applications to prestigious programs, are underconfident students more sensitive to rank feedback than overconfident students? We might expect so as high-achieving students, that is, those most likely to apply to prestigious tracks, are overrepresented among underconfident students. The results reported in Table A.5 show that the treatment reduces the impact of misconfidence for both underconfident and overconfident students (with the coefficients being more precisely measured for overconfidence). However, as expected, boosting the confidence of underconfident students plays a larger role in the likelihood of applying to an elite program (CPGE) and of being admitted to one than decreasing the confidence of overconfident students.

This last result raises an important question. If boosting the confidence of underconfident students increases their ambition, does that help close the gender and social aspiration gaps we document in section 4.1 among high-achieving students?

6.2 Correcting misconfidence reduces aspiration gaps

To test whether rank feedback helps close the aspiration gap among high-achieving students, we focus on the students who received the highest honors.[42] For the great majority of these students (92%), our rank feedback informs them that their GPA rank is better than they thought. Moreover, the feedback treatment confirms that they are at the top of

[42]Note that the focus on highest honors students was not specified in the pre-registration as we did not expect most of the variation in self-confidence and in the prestige of applications by gender and social background to come from high-achieving students. Hence, the following analysis is motivated by our findings in the first part of the paper.

the distribution, which may give an additional boost to students with high, but imprecise, prior beliefs. Recall that among highest honors students, female and low-SES students are significantly less confident than their male and high-SES counterparts. This suggests that providing feedback may have the greatest impact on this particular group of students.

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

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

and

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

$\mathrm{Feedback}_i$ 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. $\mathrm{Feedback}_i$ is equal to zero for students who do not receive feedback. $\mathrm{Low\text{-}SES}_i$ 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 and includes 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 feedback on the gender aspiration gap. The results, reported in Table 4 show that the feedback treatment helps close the gender and social aspiration gaps. Starting with the gender gap, Panel A of Table 4 shows stronger treatment effects for high-achieving females than for high-achieving males. While the treatment does not significantly affect the college applications of high-achieving male students, high-achieving females ap-

Table 4: Effect of correcting misconfidence on gender and social aspiration gaps (highest honors students)

	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
Panel A: By gender						
Female	-0.502***	-0.101	-0.541***	-0.330***	-0.450***	-0.284***
	(0.086)	(0.127)	(0.123)	(0.065)	(0.168)	(0.080)
Rank feedback	-0.081	-0.043	-0.233*	-0.122	-0.150	-0.066
	(0.066)	(0.149)	(0.139)	(0.078)	(0.205)	(0.105)
Rank feedback × Female	0.397***	0.033	0.451**	0.200*	0.368	0.206*
	(0.118)	(0.170)	(0.174)	(0.102)	(0.262)	(0.120)
Constant	1.794***	-0.886***	0.082	0.042	-1.223	0.022
	(0.563)	(0.275)	(0.535)	(0.265)	(1.200)	(0.262)
Real rank (admin)	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.155	0.010	0.153	0.085	0.095	0.051
Observations	320	320	320	320	298	298
Mean outcome	3.156	-0.203	1.787	0.631	2.125	0.275
Panel B: By SES						
Low-SES	-0.635***	-0.267**	-0.689***	-0.303***	-0.838***	-0.226***
	(0.186)	(0.115)	(0.154)	(0.088)	(0.229)	(0.056)
Rank feedback	0.109	-0.037	0.038	-0.040	0.009	0.042
	(0.071)	(0.080)	(0.091)	(0.059)	(0.138)	(0.062)
Rank feedback × Low-SES	0.446**	-0.001	0.139	0.324**	0.313	0.214*
	(0.225)	(0.147)	(0.211)	(0.141)	(0.361)	(0.123)
Constant	1.625***	-0.846***	-0.081	-0.084	-1.272	-0.135
	(0.490)	(0.293)	(0.504)	(0.273)	(1.174)	(0.270)
Real rank (admin)	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.181	0.033	0.197	0.062	0.141	0.028
Observations	315	315	315	315	294	294
Mean outcome	3.158	-0.201	1.790	0.635	2.125	0.279

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 received the highest honors. In Column (1), the dependent variable is the z-standardized maximal prestige (in terms of the 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, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the outcome is the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. Only students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1,^{**} < .05,^{***} < .01$.

ply more ambitiously when given feedback.[43] Among the high-achieving students in our sample, our intervention closes 79% of the gender gap in the prestige of the best application (0.397/0.502); a surprisingly large effect. In Figure A.11, we go beyond average treatment effects and plot the distribution of maximum prestige, separately for the treatment and control group. The figure shows that the treatment effect is driven by a reduction in the share of females who do not apply to any prestigious program. In contrast, high-achieving male students already apply to very prestigious programs in the control group.

Moreover, Table 4 shows that the treatment also closes 61% of the gender gap in elite track (CPGE) applications. Boosting confidence not only shrinks the gender application gap, it also reduces the gender gap in admissions by 73% (feedback increases women's admissions to elite tracks by 14.0 percentage points). All in all, our 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.[44]

Effect of feedback on the social aspiration gap. We reach similar conclusions on the effect of our intervention on the social aspiration gap. Panel B of Table 4 reports heterogeneous treatment effects according to student social background. Here again, we find that correcting underconfidence has a larger effect for high-achieving low-SES students than for high-achieving high-SES students. Providing feedback on real rank closes 71% of the gap in the top program prestige. Figure A.11c shows that this treatment effect is mostly driven by reducing non-prestigious top choices among low-SES students. Finally, the treatment completely closes the gap in applications and admission to an elite track (CPGE). All in all, we observe large effects on high-achieving female and low-SES students which suggests that a simple intervention can effectively reduce the gender and SES gap in aspiration.

[43] Interestingly, although male highest honors students also mostly receive positive information on their rank, we find no treatment effects for male students.

[44] For completeness, in Table A.7, we show the corresponding results for the students who did not obtain the highest honors. For these students, we find that the rank feedback reduced the gender gap to a lesser extent and not significantly so. Moreover, we find that the treatment had an insignificant positive impact on admissions to CPGE for male students, but no impact for female students ($-0.046 + 0.040 = -0.006$).

7 Mechanism: Confidence and perceived admission chances

In this section, we use our survey data to shed light on two channels through which confidence can affect college choice: student perception of their admission chances and their perception of success in a program. Our results mostly point to the former channel, thereby complementing recent literature on the importance of incorrect beliefs about admission chances (Agarwal and Somaini, 2018; Kapor et al., 2020; Tincani et al., 2022; Larroucau et al., 2021; Arteaga et al., 2022).

Outcomes. We use three outcomes to analyze these channels:

1. Guessed match. In the very last part of the survey (i.e., after the information treatment), we asked students to bet on the program they expected to enroll in at the end of the admission process. The bet reflects the program that students anticipate enrolling in from the set of programs they believe they will receive an offer from. As an outcome, we consider the prestige of this program (prestige is defined, as before, by the average GPA of the students enrolled in this program). This outcome could be affected both by the probability to receive an offer and by the probability to accept a potential offer. Next, we disentangle these two channels.

2. Acceptance conditional on offer. We observe both the offers made by each program and whether students accept or reject each offer. We study whether the probability to accept a prestigious offer (from a program in the top 10% of the prestige distribution or a CPGE) depends on misconfidence and whether it is affected by the rank feedback.

3. Perceived admission chances. In the survey, we ask 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." We asked students about their perceived admission chances before the randomized intervention, so we can use offer beliefs as a pre-determined student characteristic.[45] We look at student overall beliefs about admission chances (i.e., across all programs they applied to), but also at their beliefs regarding prestigious programs. Misperception of admission chances to prestigious

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

programs can be more costly, especially for the best students. We, therefore, consider student beliefs of their admission chances for (i) programs in the top 10% of the prestige distribution and (ii) elite programs (CPGE).

Effect of rank feedback on guessed match. Columns (1) and (2) of Table 5 show how much the prestige of the guessed match depends on misconfidence and how much our feedback treatment affects the role played by confidence.[46] The results reported in Column (1) show that more confident students believe they will end up attending more prestigious programs; controlling for true ability. A 10 percentile higher confidence is associated with a bet on a 0.06 SD more prestigious program. The feedback treatment reduces this large effect of misconfidence by 67% (column (2)).

The guessed match captures both the probability to receive an offer from a program and the propensity to accept an offer. The next two variables help to disentangle these two channels.

Acceptance conditional on offer. Conditional on receiving an offer from a prestigious program, students may be more or less inclined to accept the offer based on their confidence to succeed in the program. To study this mechanism, we regress the probability to accept a prestigious offer on misconfidence and a student correct rank. We only consider the control group for these regressions as the treatment may affect both the numerator and the denominator of the dependent variable.

Columns (3) and (4) of Table 5 show the results. Overall, we do not find strong evidence that the propensity to accept a prestigious offer is correlated with misconfidence. The coefficients are insignificant and close to zero.

Perceived admission chances. Finally, to check whether student misconfidence affects perceived admission chances, we use a similar specification as in Section 5, Equation (2):

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

[46]For this analysis, we exclude participants who indicated an offer belief of 0 or 100 since beliefs can only be shifted in one direction for these participants. 258 students betted on a program to which they assign an offer probability of 100 percent, and 2 students betted on a program to which they assign an offer probability of 0 percent.

Table 5: Effect of confidence and feedback treatment on the prestige of guessed match and acceptance conditional on offer

			Acceptance given offer	
	Prestige of guessed match		CPGE	Top 10%
	(1)	(2)	(3)	(4)
Misconfidence	0.580**	0.546***	0.074	0.162
	(0.242)	(0.209)	(0.228)	(0.308)
Rank feedback		0.074		
		(0.057)		
Rank feedback				
× Misconfidence		-0.368*		
		(0.222)		
Sample	Control	Total	Control	Control
Real rank (pre-survey)	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓
Adj. R2	0.269	0.280	0.017	0.005
Observations	833	1569	192	121

Notes: Rank 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 Columns (1) and (2), the dependent variable is the prestige of the guessed outcome (based on the incentivized bet on the final match). We do not include respondents who state they have 0 or 100 percent probability of receiving an offer from the program they bet on since their beliefs are bounded. In Columns (3) and (4), 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 $^{*} < .1$, $^{**} < .05$, $^{***} < .01$.

Table 6: 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 (admin)	✓	✓	✓	✓	✓	✓
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 effect of misconfidence on student 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 on 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. Only students from *bac général* are included. Standard errors are clustered at the student level. Significance levels are indicated by $^* < .1, ^{**} < .05, ^{***} < .01$.

where observations are now at the student-program level. The outcome (Y_{ij}) measures student i's belief that she will receive an offer from program j. More confident students may apply to more competitive programs with lower admission chances, which would bias the estimate of β_1. To avoid this selection, W_j includes controls for the prestige of the programs a student is applying to (both linearly and using a quadratic term). All regressions also control for student real rank and a set of honor fixed effects. We cluster standard errors at the student level.

Table 6 reports the results. In Column (1) and (2), we look at whether misconfidence is correlated with students' beliefs in their chances of receiving an offer, controlling for ability and program prestige. A 10 percentile higher confidence increases a student's belief that she will receive an offer from a program she applied to by 7.0 percentage points.[47] In Columns (3) to (6), we focus on beliefs about receiving an offer from the most prestigious programs. For these programs, confidence plays an even larger role in perceived admission chances. A 10 percentile higher confidence increases a student's belief that she will receive an offer from one of the top 10% most prestigious programs by 10.3 percentage points, and from a CPGE by 14 points.

All in all, our results show that, above and beyond a student's ability, the more confident a student is, the larger she perceives her college admission chances at competitive programs to be. This suggests that our intervention, by correcting under- and over-confidence, may have affected students' applications primarily 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 aspirations 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 self-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 misconfidence matters for college applications. The intervention also substantially reduces the gender and social gap in the prestige of the applications and in the likelihood of applying to elite programs (CPGE). These results show that misconfidence has a clear and large causal effect on the prestige of students' applications and on their final assignments.

[47] 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.

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 aspiration gaps.

Finally, our results suggest that correcting underconfidence is more critical than correcting overconfidence. A natural policy recommendation is to target feedback to the best students to encourage them to apply to the best programs, hence mitigating the gender and SES gap in elite programs. Informing students that they are overconfident might be particularly useful when there is a high chance they will aim too high and end up unassigned, typically in countries where most colleges are oversubscribed. In such an environment, providing feedback to both under- and overconfident students is important.

Our strong feedback effect raises questions about when and why we can expect effects of similar size. A key consideration is whether a country has a standardized nationwide college entrance test, which implies that students have a more accurate knowledge of their position in the nationwide distribution. There is no college entrance test in France, which is true for many other countries, like Austria, Belgium, Canada, Italy (except for some subjects), Mexico, the Netherlands, Germany, Denmark, Finland, and others.[48] In these countries, we surmise that our intervention would have an effect of similar size, if not larger, as students, unlike in France, are often not aware of their within-class GPA rank, which might increase student misperception of their position in the national distribution.

In contrast, in many countries, students know their scores in a centralized exam before they start college applications, for instance, in Hungary, Chile, China, Brazil, and Australia. Thus, students might easily infer their rank, and misconfidence is likely to be smaller than in our context. The rank is sometimes even communicated directly to students with the results of the centralized exam, as in some provinces of China.[49] In these environments, our intervention might have a smaller effect.[50] Interestingly, recent papers show that centralized exams might hurt girls, as they tend to underperform under pressure (Cai et al., 2019; Arenas and Calsamiglia, 2022). Our results suggest that centralized ex-

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

[49]In some provinces of China, students have access to the exact rank of their score nationwide and in the province. The latter is relevant due to the regional quotas of universities. See for example, `https://www.gk100.com/read_70367.htm` (in Chinese, retrieved 11/7/2022).

[50]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.

amination has pros and cons as it can also help to fight girls' tendency to underconfidence in sparse-information environments.

Our results are relevant for policymakers who design school and college admission processes. The design of admission markets is often limited to the selection of an appropriate mechanism, whereas our results suggest that stopping there is not sufficient. Policymakers also need to carefully consider which information should be provided to students to allow them to fully express their preferences. Otherwise, the desired market outcomes (e.g., stability) might not be reached. This conclusion is based on a rich literature that shows the importance of providing historical cutoff grades (Immorlica et al., 2020; Hakimov et al., forthcoming), information about the quality of the programs (Hastings and Weinstein, 2008), and admission chances (Kapor et al., 2020). Our easy-to-scale intervention adds to the options of the designer and allows for cheap mitigation of the pre-existing gender and social inequalities among high-achieving students.

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.

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.

Arenas, Andreu and Caterina Calsamiglia, "Gender differences in high-stakes performance and college admission policies," September 2022. https://drive.google.com/file/d/1qDMbmaElDeow_2dWJn6PMwWuWdFJ8uga/view (retrieved 11/6/2022).

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.

Bandiera, Oriana, Nidhi Parekh, Barbara Petrongolo, and Michelle Rao, "Men are from Mars, and women too: a Bayesian meta-analysis of overconfidence experiments," *CEP Discussion Paper 1820*, December 2021.

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, "Top percent policies and the return to postsecondary selectivity," *Research & Occasional Paper Series: CSHE*, 2021, *1.*

Bó, Inácio and Rustamdjan Hakimov, "Pick-an-object mechanisms," *Management Science*, forthcoming.

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," April 2023. https://veronicafrisancho.files.wordpress.com/2019/05/perceivedability_schoolchoice_apr2019.pdf (retrieved 01/19/22).

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," Technical Report, Tech. rep. Working Paper 2016.

Bruhin, Adrian, Fidel Petros, and Luıs Santos-Pinto, "The role of self-confidence in teamwork: Experimental evidence," Technical Report, Working paper 2022.

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, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan, "Mobility Report Cards: The Role of Colleges in Intergenerational Mobility," Working Paper 23618, National Bureau of Economic Research July 2017.

Cortés, Patricia, Jessica Pan, Ernesto Reuben, Laura Pilossoph, and Basit Zafar, "Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and Lab," *The Quarterly Journal of Economics*, forthcoming.

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.

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.

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).

— **,** — **, Hannah Schildberg-Hörisch, and Florian Zimmermann**, "Self-Assessment: The Role of the Social Environment," May 2020. https://rationality-and-competition.de/wp-content/uploads/2020/05/244.pdf (retrieved 01/19/2022).

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.

Gillen, Ben, Erik Snowberg, and Leeat Yariv, "Experimenting with Measurement Error: Techniques with Applications to the Caltech Cohort Study," *Journal of Political Economy*, 2019, *127*, 1826–1863.

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

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.

— , — , and — , "Costly information acquisition in centralized matching markets," *Quantitative Economics*, forthcoming.

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.

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 Kreiner, and Stefanie Stantcheva, "Social Positions and Fairness Views on Inequality," *The Review of Economic Studies*, forthcoming.

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.

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*, forthcoming.

_ **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*, forthcoming.

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

_ , "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.

Tincani, Michela M., Fabian Kosse, and Enrico Miglino, "The Effect of Preferential Admissions on the College Participation of Disadvantaged Students: The Role of Pre-College Choices," *Working Paper*, October 2022.

van Veldhuizen, Roel, "Gender Differences in Tournament Choices: Risk Preferences, Overconfidence, or Competitiveness?," *Journal of the European Economic Association*, 2022, *20* (4), 1595–1618.

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

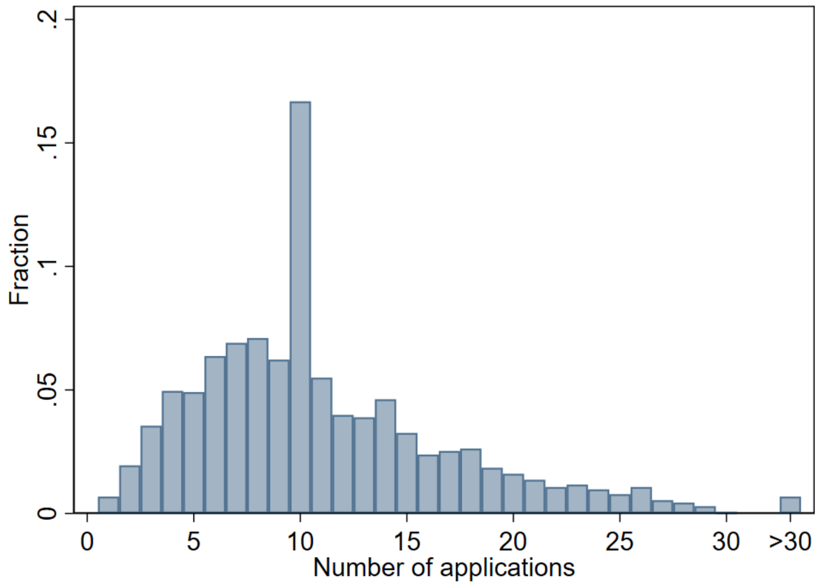
A Additional Tables and Figures

Table A.1: Balance table

		Main survey			
	Admin data	Total	Control	Feedback	Difference (p-value)
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: The table shows the balance of descriptive statistics in the administrative data and in the survey (total, control, and grade feedback treatment). The final column shows the p-value of a t-test comparing the treatment and control group. For comparability, only *bac général* students who graduated in 2021 are considered. Region refers to educational districts (*académie*) in which the respondent went to high school. Share disadvantaged is the share of individuals who receive a state scholarship to study in that district. Finally, the table shows a number of survey measures that we elicited 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 (guessed rank minus real rank), misconfidence by honors, overconfidence (guessed rank minus real rank, only for overconfident students), and underconfidence (real rank minus guessed rank, only for underconfident students).

Figure A.1: Number of applications



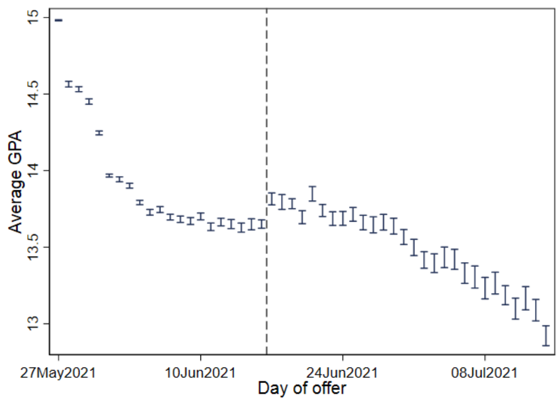
Notes: The figure shows a histogram of the number of applications that graduates from the general high school track submitted in 2021 (using the administrative data). We group together choices that are considered as one choice by the platform.

Table A.2: Application behavior in the administrative data and in the survey control group

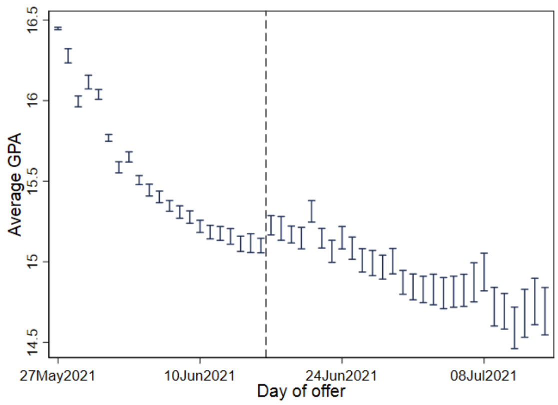
	Admin data	Survey (Control)
Panel A: Application list		
Max(prestige)	2.390	2.290
	(1.106)	(1.129)
Min(prestige)	-0.625	-0.519
	(0.570)	(0.527)
Mean(prestige)	0.893	0.873
	(0.908)	(0.886)
One CPGE	0.266	0.271
	(0.442)	(0.445)
Number of applications	11.244	10.830
	(6.3311)	(5.865)
Number of observations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

Notes: The table shows means and standard deviations (in parentheses) of characteristics of the application list (Panel A) and the final outcome (Panel B). Since these outcomes are determined post-treatment, we focus on the survey control group. Max(prestige), Min(prestige), and Mean(prestige) refer to the maximal, minimum, and mean prestige of the application list (in terms of average grades of admitted students), respectively. Prestige is defined at the program level as the z-transformed average grade of admitted students. One CPGE means that the student included one elite track in the application list.

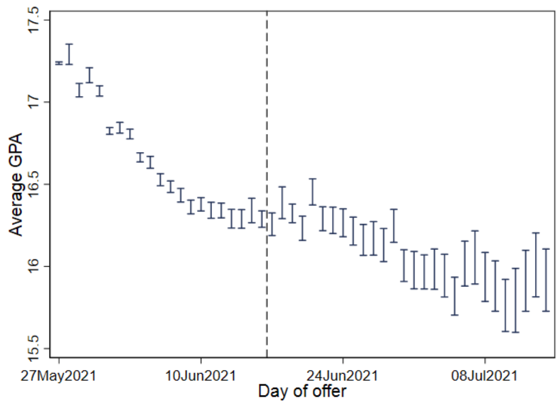
Figure A.2: Average GPA by day of offer



(a) All programs



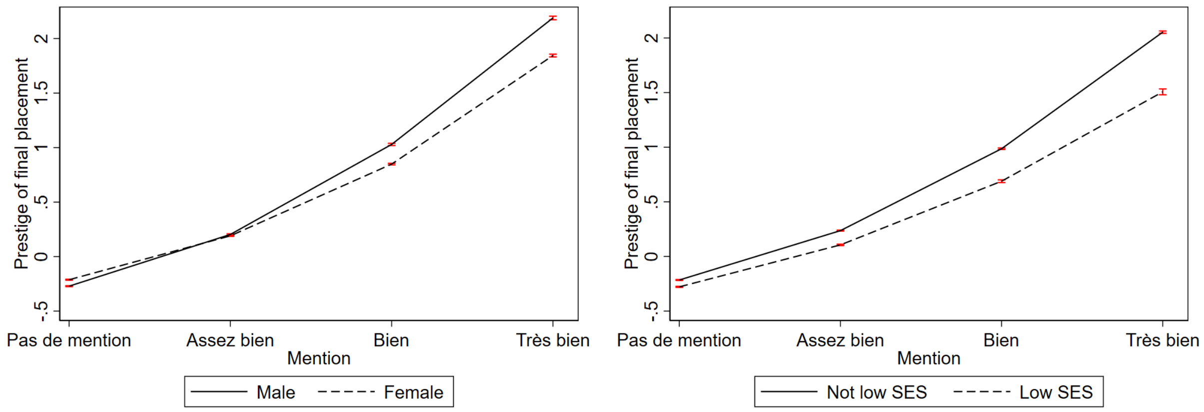
(b) Only CPGE



(c) Only Top 10% prestige

Notes: The 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 same 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. Note that offers on the first day can be held for 4 days, on the second day for 3 days, and later offers for two days. Panel (a) includes offers from 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: Prestige of accepted program by honors and gender/SES

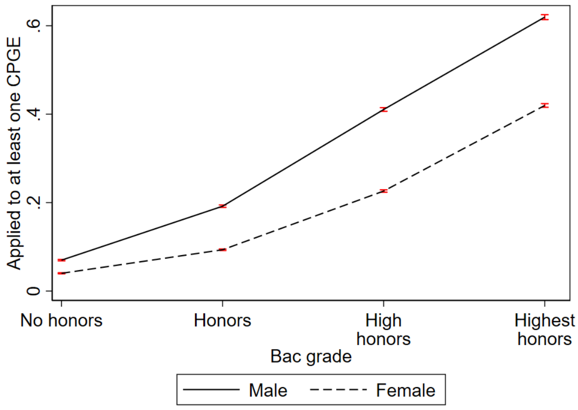


(a) Prestige by gender

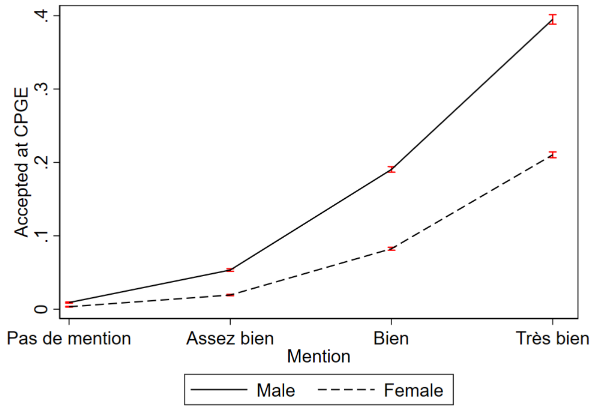
(b) Prestige by SES

Notes: The figures show the prestige of the final match by honors level and gender/SES. Prestige of a program is defined as the mean grade level of all enrolled students. Bars indicate 95% confidence intervals.

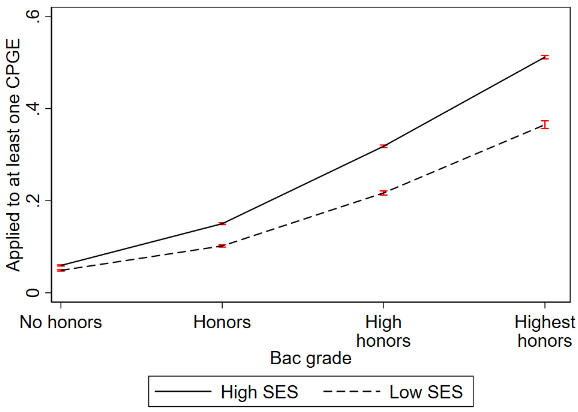
Figure A.4: Applications and admission to CPGE by honors and gender/SES



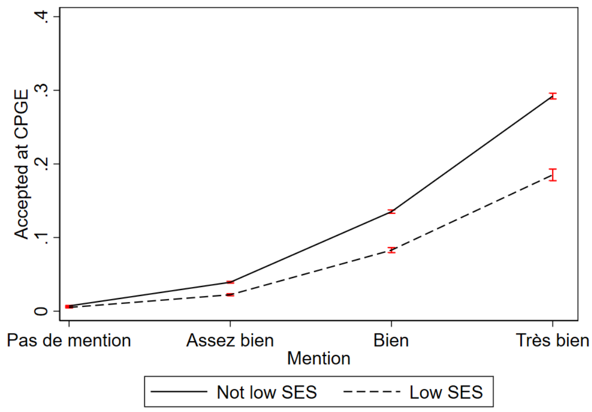
(a) Applied to CPGE by gender



(b) Matched to CPGE by gender



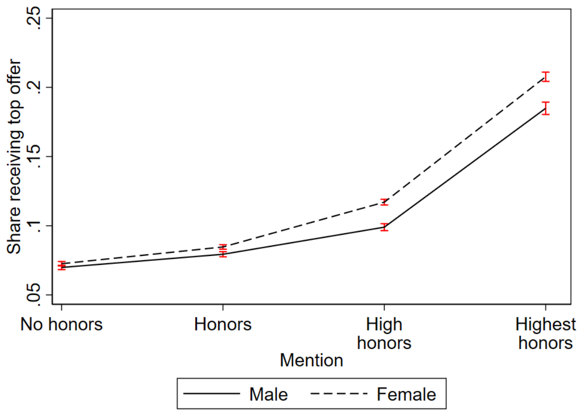
(c) Applied to CPGE by SES



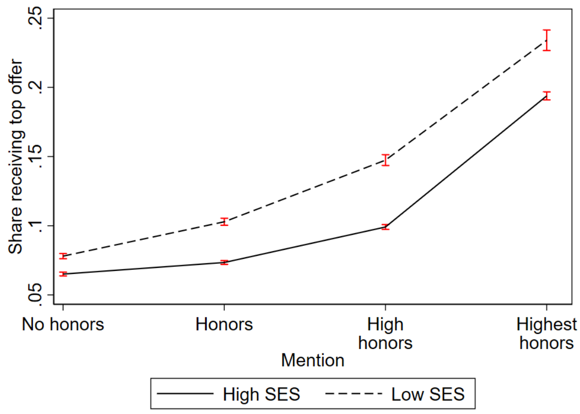
(d) Matched to CPGE by SES

Notes: The figures show the propensity to apply to a preparatory class (CPGE) and to be ultimately matched to a CPGE by honors level and gender/SES. The 95% confidence intervals are based on predicted values from a regression on the interaction of honors level and female/low SES.

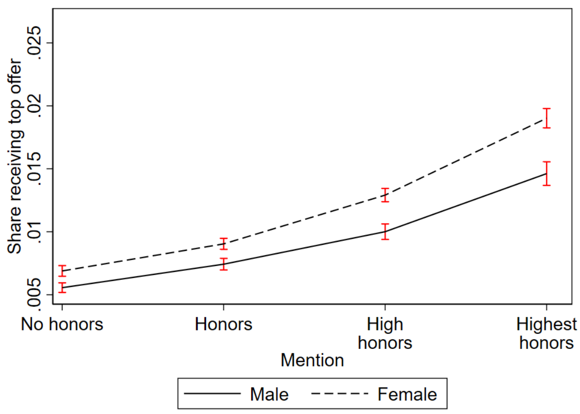
Figure A.5: Probability of being accepted at the top program by gender and SES



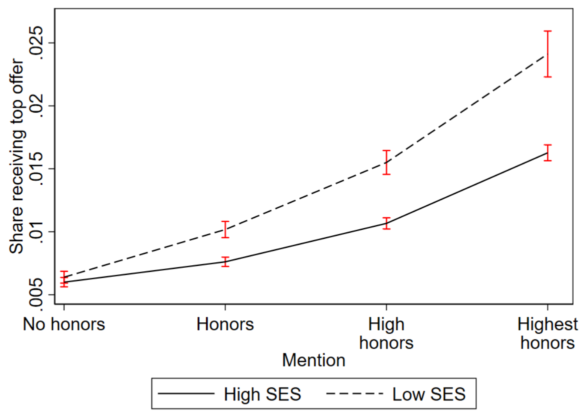
(a) By gender



(b) By SES



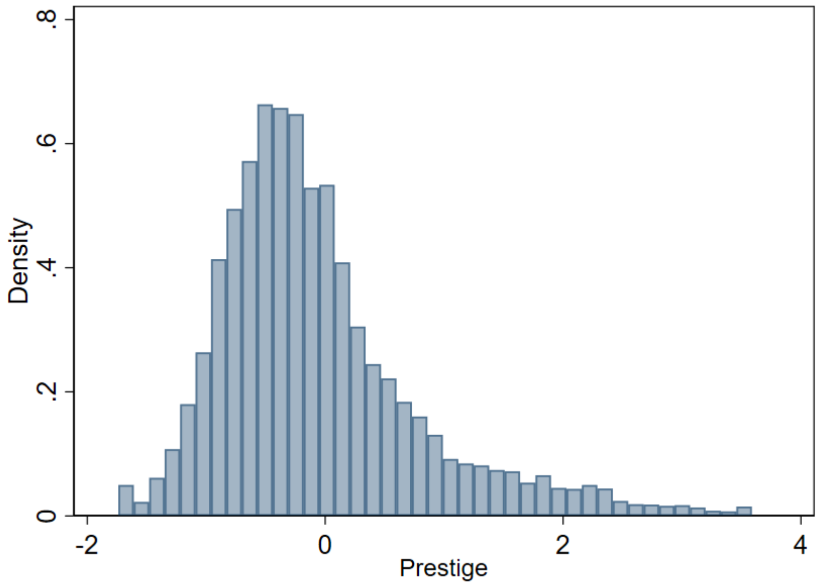
(c) By gender (only first day offers)



(d) By SES (only first day offers)

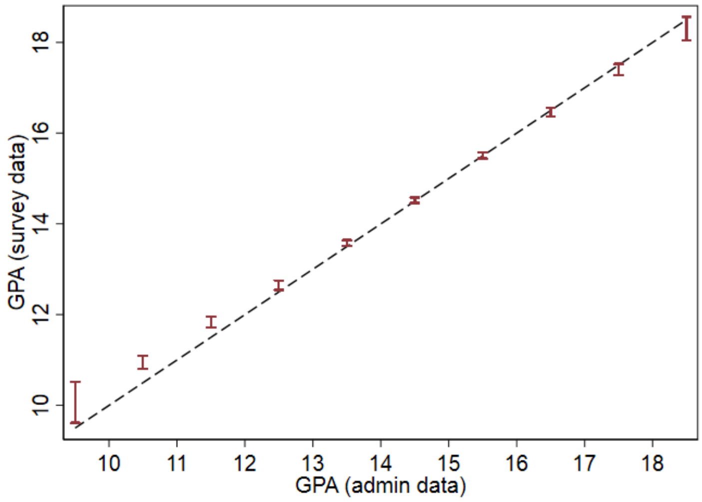
Notes: The figures show the probability that a student receives an offer from the most prestigious program in her application list, by Bac grade and gender/SES. In Panel (a) and (b), we consider all offers, while in Panel (c) and (d), we only consider offers that are made on the first day (to control for differences in the timing of exit). Bars indicate 95% confidence intervals.

Figure A.6: Distribution of program prestige



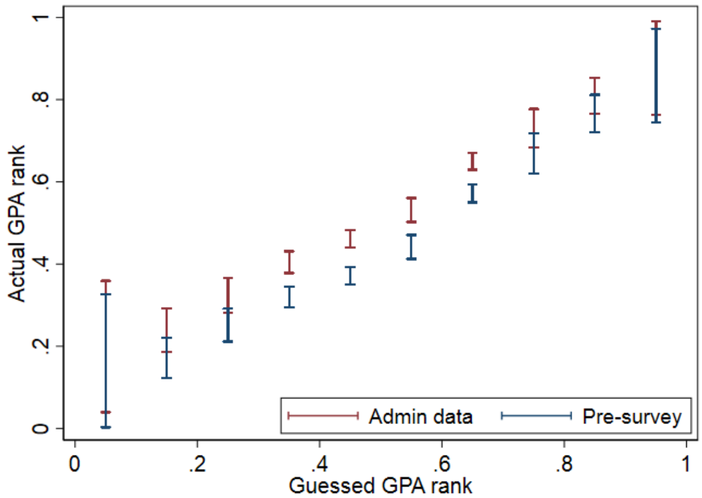
Notes: The figure shows a histogram of the prestige measure. Programs are the unit of observation. Prestige is defined at the program level as the mean *bac* grade of all admitted students. Prestige is z-standardized by subtracting the mean among all programs in the dataset and dividing by their standard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

Figure A.7: Reported GPA (main survey) vs. real GPA (admin data)



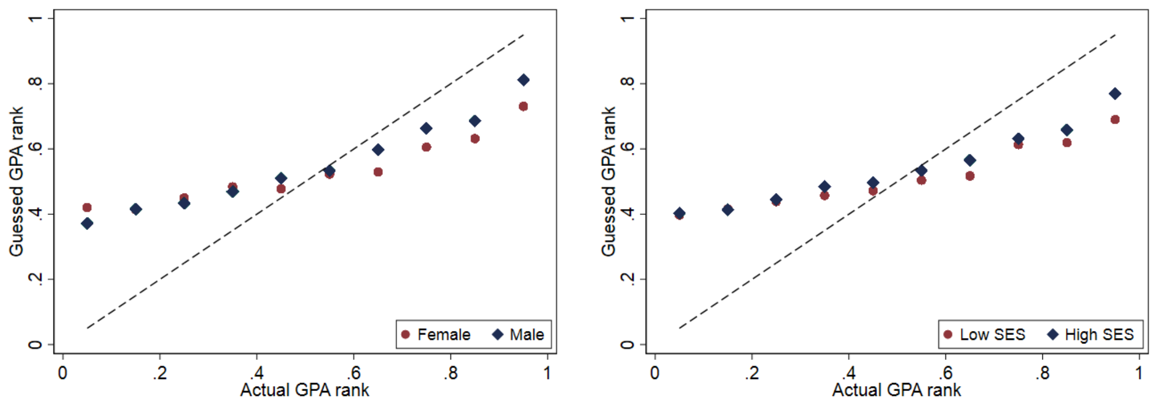
Notes: The figure shows the mean self-reported GPA in the main survey (Y-axis) by GPA in the admin data (X-axis). Students with a GPA below 10 are grouped in the leftmost category and students with a GPA above 18 in the rightmost category. The dashed line represents the 45-degree line. Bars indicate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

Figure A.8: 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.9: Guessed GPA rank by real rank



(a) Guesses by gender

(b) Guesses by SES

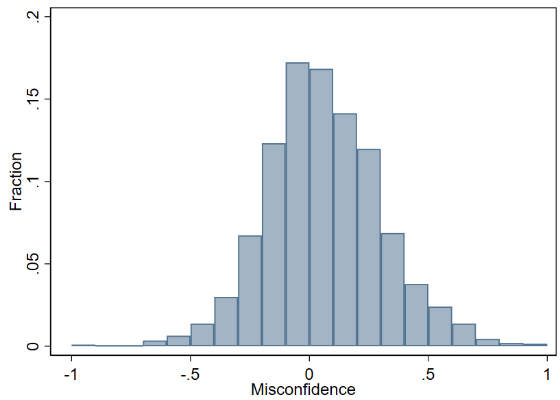
Notes: The figure shows the guessed GPA rank by real GPA rank (measured using the grade distribution from the pre-survey). The dots are mean guesses in bins of 10 ranks each. If respondents' stated guesses were accurate, they would be on the dotted 45 degree line.

Table A.3: Confidence gaps by gender and SES (GPA distribution from pre-survey)

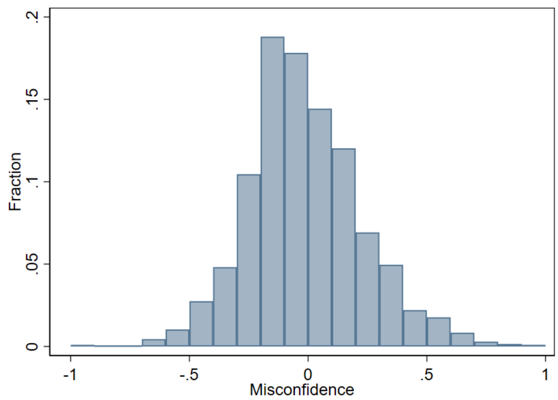
	Misconfidence	Underconfidence	Overconfidence
Panel A: Female coefficient			
Total	-0.018**	0.028**	0.015*
	(0.007)	(0.010)	(0.008)
	[2034]	[852]	[1138]
By honors			
No honors	0.037**	0.008	0.043***
	(0.016)	(0.030)	(0.017)
	[473]	[28]	[438]
Honors	-0.020*	0.002	-0.006
	(0.011)	(0.013)	(0.011)
	[690]	[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: Low SES coefficient			
Total	-0.020**	0.035***	0.006
	(0.008)	(0.010)	(0.009)
	[2000]	[840]	[1116]
By honors			
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)	(0.156)	(0.012)
	[544]	[333]	[185]
Highest honors	-0.047**	0.060**	0.039
	(0.024)	(0.023)	(0.031)
	[314]	[289]	[20]
True rank (pre-survey)	✓	✓	✓

Notes: The table reports the OLS coefficients from regressing the misconfidence variable (guessed rank minus the real rank), the underconfidence variable (negative misconfidence if underconfident), and the overconfidence variable (misconfidence if overconfident) on a female indicator (in Panel A) and a low SES indicator (in Panel B), while controlling for real rank. Real rank in these estimations is based on the pre-survey reference group. The regressions are conducted on the total sample and split by honors categories. Robust standard errors are in round parentheses and the number of observations in square brackets. Significance levels are indicated by $* < .1, ** < .05, *** < .01$.

Figure A.10: Distribution of misconfidence



(a) Real rank based on pre-survey



(b) Real rank based on admin data

Notes: The 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.

Table A.4: Association between misconfidence and college applications and admissions by treatment

	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
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: Misconfidence is the difference between the guessed rank and the real rank. In Column (1), the dependent variable is the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list, in Column (2), minimum prestige of the application list, in Column (3) the average prestige of the application list, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the outcome is the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. Only the treatment group and students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1,^{**} < .05,^{***} < .01$.

Table A.5: Treatment effect of Grade feedback on outcomes (by under-/overconfidence)

	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
Underconfidence	-0.461	-0.257	0.484*	-0.478***	-0.445	-0.276***
	(0.287)	(0.169)	(0.249)	(0.137)	(0.328)	(0.088)
Rank feedback × Underconfidence	0.103	0.124	0.227	0.321*	-0.070	0.254*
	(0.363)	(0.211)	(0.319)	(0.190)	(0.458)	(0.153)
Overconfidence	0.711***	-0.000	0.376**	0.128*	0.400**	0.046
	(0.252)	(0.100)	(0.148)	(0.075)	(0.197)	(0.045)
Rank feedback × Overconfidence	-0.719**	0.040	-0.269	0.035	-0.211	-0.002
	(0.301)	(0.124)	(0.186)	(0.093)	(0.253)	(0.066)
Rank feedback	0.107	-0.006	0.041	-0.042	0.027	0.002
	(0.068)	(0.036)	(0.051)	(0.028)	(0.068)	(0.022)
Constant	1.376***	-0.786***	0.091	-0.019	-0.532***	-0.040**
	(0.091)	(0.040)	(0.056)	(0.027)	(0.070)	(0.017)
Real rank (pre-survey)	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Observations	2033	2033	2033	2033	1793	1793

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. In Column (1), the dependent variable is the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list, in Column (2), minimum prestige of the application list, in Column (3) the average prestige of the application list, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the outcome is the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. Only students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1,^{**} < .05,^{***} < .01$.

Table A.6: Effect of correcting misconfidence on college applications and admissions

	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
Misconfidence	0.620***	0.101	0.443***	0.276***	0.472***	0.149***
	(0.168)	(0.079)	(0.118)	(0.064)	(0.161)	(0.046)
Rank feedback	0.015	0.005	0.018	-0.018	-0.006	0.017
	(0.044)	(0.022)	(0.032)	(0.017)	(0.040)	(0.013)
Rank feedback × Misconfidence	-0.483***	-0.018	-0.260**	-0.097	-0.122	-0.104**
	(0.182)	(0.083)	(0.125)	(0.068)	(0.173)	(0.052)
Constant	1.335***	-0.823***	0.027	-0.070***	-0.622***	-0.069***
	(0.077)	(0.036)	(0.050)	(0.026)	(0.065)	(0.018)
Real rank (admin)	✓	✓	✓	✓	✓	✓
Honors FE	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.227	0.119	0.334	0.197	0.460	0.102
Observations	2034	2034	2034	2034	1793	1793
Mean outcome	2.292	-0.521	0.874	0.260	0.691	0.098

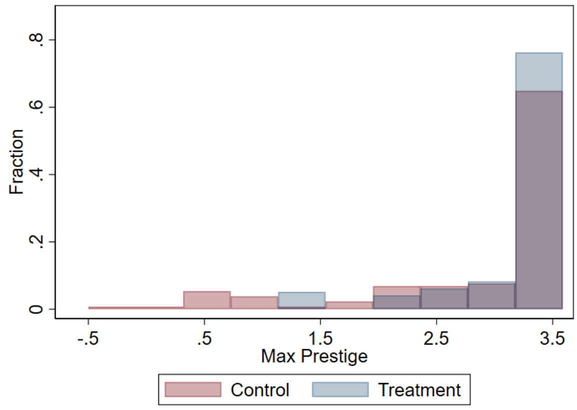
Notes: This table reports OLS estimates of the effect of the intervention (rank feedback) on the role played by confidence in student college choices. Feedback is a dummy variable that is equal to one for the randomly-selected group of students who received information on their real rank in the ability 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. In Column (1), the dependent variable is the z-standardized maximal prestige (in terms of average grades of admitted students) of the application list, in Column (2), minimum prestige of the application list, in Column (3) the average prestige of the application list, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the outcome is the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. Only students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1,^{**} < .05,^{***} < .01$.

Table A.7: Effect of correcting misconfidence on gender and social aspiration gaps (without highest honors students)

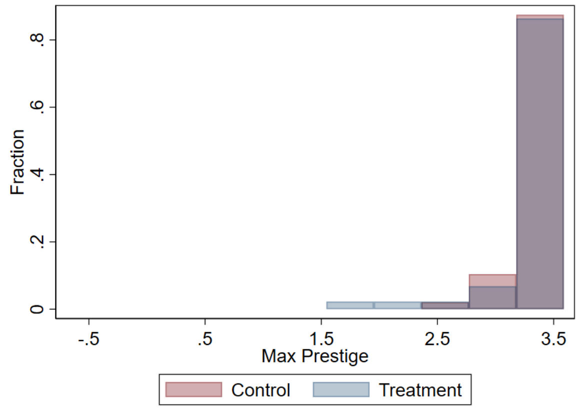
	Application list				Final match	
	(1) Max Prestige	(2) Min Prestige	(3) Mean Prestige	(4) One CPGE	(5) Prestige	(6) CPGE
Panel A: By gender						
Female	-0.265***	0.013	-0.158***	-0.139***	-0.123**	-0.059***
	(0.071)	(0.033)	(0.049)	(0.027)	(0.060)	(0.018)
Rank feedback	-0.107	-0.015	-0.046	-0.032	-0.064	0.040
	(0.076)	(0.037)	(0.055)	(0.032)	(0.069)	(0.025)
Rank feedback × Female	0.164	0.041	0.094	0.026	0.076	-0.046*
	(0.100)	(0.047)	(0.070)	(0.038)	(0.087)	(0.028)
Constant	1.598***	-0.806***	0.209***	0.083***	-0.464***	-0.004
	(0.069)	(0.032)	(0.046)	(0.026)	(0.058)	(0.016)
	(0.069)	(0.032)	(0.046)	(0.026)	(0.058)	(0.016)
Real rank (admin)	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.133	0.056	0.177	0.102	0.263	0.069
Observations	1732	1732	1732	1732	1510	1510
Mean outcome	2.132	-0.580	0.705	0.193	0.407	0.064
Panel B: By SES						
Low-SES	-0.267***	-0.059*	-0.151***	-0.025	-0.104*	-0.018
	(0.079)	(0.033)	(0.051)	(0.027)	(0.062)	(0.016)
Rank feedback	-0.028	0.004	0.011	-0.004	-0.006	0.018
	(0.059)	(0.029)	(0.043)	(0.023)	(0.052)	(0.016)
Rank feedback × Low-SES	0.043	0.029	0.000	-0.039	-0.045	-0.016
	(0.109)	(0.048)	(0.072)	(0.037)	(0.090)	(0.024)
Constant	1.559***	-0.774***	0.181***	0.015	-0.493***	-0.029**
	(0.064)	(0.029)	(0.041)	(0.021)	(0.053)	(0.013)
Real rank (admin)	✓	✓	✓	✓	✓	✓
Risk preference	✓	✓	✓	✓	✓	✓
Adj. R2	0.138	0.056	0.182	0.081	0.268	0.043
Observations	1703	1703	1703	1703	1483	1483
Mean outcome	2.133	-0.579	0.706	0.193	0.408	0.064

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. In Column (1), the dependent variable is the z-standardized maximal prestige (in terms of the 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, and in Column (4) an indicator of whether at least one CPGE is included in the list. In Column (5) the outcome is the prestige of the final match and in Column (6) it is an indicator of whether the final match is a CPGE. Only students from *bac général* are included. Robust standard errors in parentheses. Significance levels are indicated by $^{*} < .1,^{**} < .05,^{***} < .01$.

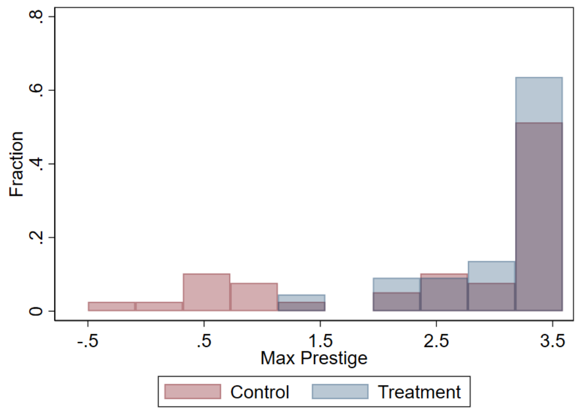
Figure A.11: Maximum prestige of highest honor students by gender and SES



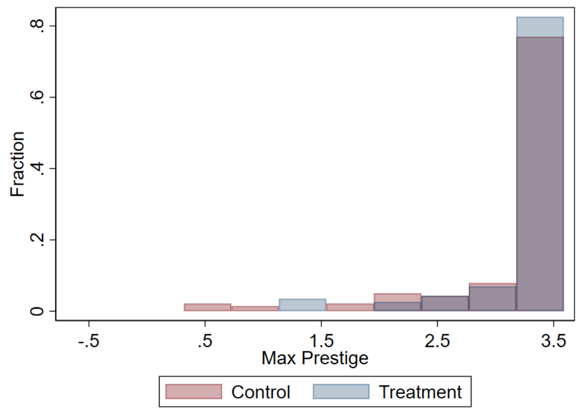
(a) Female students



(b) Male students



(c) Low-SES students



(d) High-SES students

Notes: The figure shows the distribution of the maximum prestige of the application list by treatment and control. Figures show highest honor students by gender and SES, respectively. The histograms display ten equal-sized bins.

B Alternative measures to program prestige

In the first column of Table B.1, we show the 15 most prestigious programs denoted by their type.[51] As expected, the 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

	Program type	
	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: The table shows the program type of the 15 most prestigious programs (according to the average *bac* grade of the admitted students) and the 15 programs with the lowest access rate. Only programs to which at least 10 survey participants applied are considered. The bottom row shows the average prestige and access rate of the 15 programs in the table.

A potential alternative measure for the quality of a program is the access rate (the number of available seats divided by the number of applications). While this 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. In the second column of Table B.1, we show the 15 programs with the lowest access rate, which 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 the average prestige is only 1.96 SDs. Hence, they are over-demanded, but they do not attract the best students.

[51] 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.

Another way to see this is by looking at different health-related programs. On the one hand, in 2021, more than 13,000 students accepted an offer from a nursing program. The average prestige in these programs was only 0.243 SDs, but the access rate 25.1% and, therefore, the programs are quite selective. On the other hand, more than 17,000 students accepted an offer in medical studies. Here, the average prestige was much higher (1.606 SDs), but the higher access rate (45.1%) makes it appear much less selective. Hence, by using the access rate instead of prestige, we would have wrongfully concluded that nursing programs are more prestigious than programs that prepare to become a medical doctor.

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 ambitious programs, we focus on the programs who belong to the top 10th percentile of the prestige distribution. We regress a dummy for receiving an offer on the first day on teacher-given GPAs (using dummy variables for the average GPA a student obtained). 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:

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

where the dependent variable indicates whether student i in high school k receives an offer from a top 10 prestige program j on the first day of the admission mechanism.[52] We cluster standard errors at the student level.

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 0.011. The adjusted R^2 of the specification including only the GPA indicators is equal to 0.084. Since the outcome is a dummy variable, we expect the R^2 to be low, which is why 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 0.093.

To assess the importance of grade reweighting, we calculate how many high-school fixed effects are significant. The significance of high-school fixed effects 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 the regression (6) 141 times using all high-schools that have fixed effects closest to zero (between -0.001 and +0.001) subsequently as reference schools.[53] We then average the t-statistic of the high school fixed effects over the 141 regressions.

Only 8.2 percent of fixed effects are significant on the 5% level and 15.0 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

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

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

Table C.1: Regression of offer probability at top 10 prestige programs on GPA and high-school fixed effects

	Offer 1st day		
	(1)	(2)	(3)
GPA 10-11		-0.000	0.000
		(.)	(0.001)
GPA 11-12		0.000	0.000
		(0.000)	(0.001)
GPA 12-13		0.000***	0.001
		(0.000)	(0.001)
GPA 13-14		0.001***	0.001**
		(0.000)	(0.001)
GPA 14-15		0.004***	0.005***
		(0.000)	(0.001)
GPA 15-16		0.016***	0.018***
		(0.000)	(0.001)
GPA 16-17		0.057***	0.062***
		(0.001)	(0.001)
GPA 17-18		0.140***	0.147***
		(0.002)	(0.002)
GPA >18		0.232***	0.245***
		(0.004)	(0.004)
Constant	0.036***	0.000	-0.003***
	(0.000)	(.)	(0.001)
High-school FE	✓		✓
Adj. R2	0.011	0.084	0.093
Observations	1,870,690	1,870,690	1,870,690
Applicants	180,368	180,368	180,368
Outcome mean	0.036	0.036	0.036

Notes: This table reports OLS estimates of regressing an indicator for receiving an offer from a program on the first day on GPA dummies (reference is GPA below 10) and high-school fixed effects. 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 top10 prestige program. Only students from *bac général* are included. Standard errors reported in parentheses are clustered at the student level. Significance levels are indicated by $^{*} < .1,^{**} < .05,^{***} < .01$.

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

D Data collection

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).[54] 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 provided a guess and 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, hence, 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 those participants 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.[55]

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.[56]

[54]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.

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

[56]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.

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)

Matching of survey and admin data. We match the survey data with the administrative data. To do so, we asked survey respondents for their national student number (INE).[57] Based on the INE, we can match 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 characteristics did not identify an observation uniquely, 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 hypotheses related to miscalibrated confidence, we focus on students in the general high school track (*Bac général*). The reason is that 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.

[57]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.

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.

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

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. The pre-survey took place between January 20 and February 1, 2021. We recruited subjects 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.[58]

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 was 14.0.[59] These characteristics are very similar to our main survey and the population in the admin data (cf. Table A.1). Figure A.8 further shows that the grade distribution of students in the pre-survey and in the administrative data is also close, especially among top students.

[58]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.

[59]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: The 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:

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

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 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 (forthcoming) 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. It seems as if the treatment makes students bet on programs that are less preferred according to their preference list, irrespective of their level of misconfidence. However, remember from Section 7 that the treatment made underconfident students bet on more prestigious programs and overconfident students bet on less prestigious programs. Taken together, these results suggest that underconfident students put more prestigious programs lower in their initial preference list and revise their preferences after receiving feedback. Hence, we conclude that the preferences given in the preference list should be taken with a grain of salt.

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)
Panel B: Effect of underconfidence	
Underconfidence	0.346
	(0.368)
Panel C: Effect of overconfidence	
Overconfidence	0.140
	(0.249)
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 $* < .1, ** < .05, *** < .01$.

G Main Survey Instructions (translated from French)

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

Welcome to the Parcoursup survey

You are invited to take part in a research study about applicants' behavior in Parcoursup. The study is administered by researchers at the University of Lausanne, Switzerland, and funded by the Swiss National Science Foundation (Project number 189152).

The study consists of a **survey** that we ask you to complete. **You can only participate in the survey if you plan to apply to study programs on Parcoursup in 2021**. The survey will ask you for your considerations around your application intentions and your expectations regarding the outcome.

If you participate in the survey, you will enter a sweepstake and **can win one of 40 Amazon.fr gift cards of 100 Euro** each (terms and conditions apply). You will only participate in the sweepstakes if you give complete answers. During the survey you have additional chances to win Amazon.fr gift cards of 50 Euro and 100 Euro each.

We may invite you for two more surveys in June 2021 and September 2021, for which you can earn additional gift cards.

Please note that participation in this study is entirely voluntary and that you may discontinue participation at any time. In this case, you will not be compensated.

▸ Privacy Policy

▸ Terms of Sweepstakes

Contact information

For any questions and comments, and to exercise your right to access or erase your personal data, please contact Dr Renke Schmacker at parcoursup@unil.ch.

If you agree to participate in this study, please give your consent by checking the box below.

I have read and understood the Privacy Policy and the Terms of the Sweepstakes, and I consent to participate in this study

No, I do not consent to participate in this study.

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

Please answer the following questions about yourself.

Please insert your first name and last name

First name

Last name

What is your birth date?

Year

Month

Day

What is your sex?

Male

Female

Other

What is your ZIP code?

Please name the school that you attend.

To be able to take part in the sweepstakes, we need your contact details to send you the voucher in case of winning. Please decide whether you prefer to be contacted via eMail or phone (SMS).

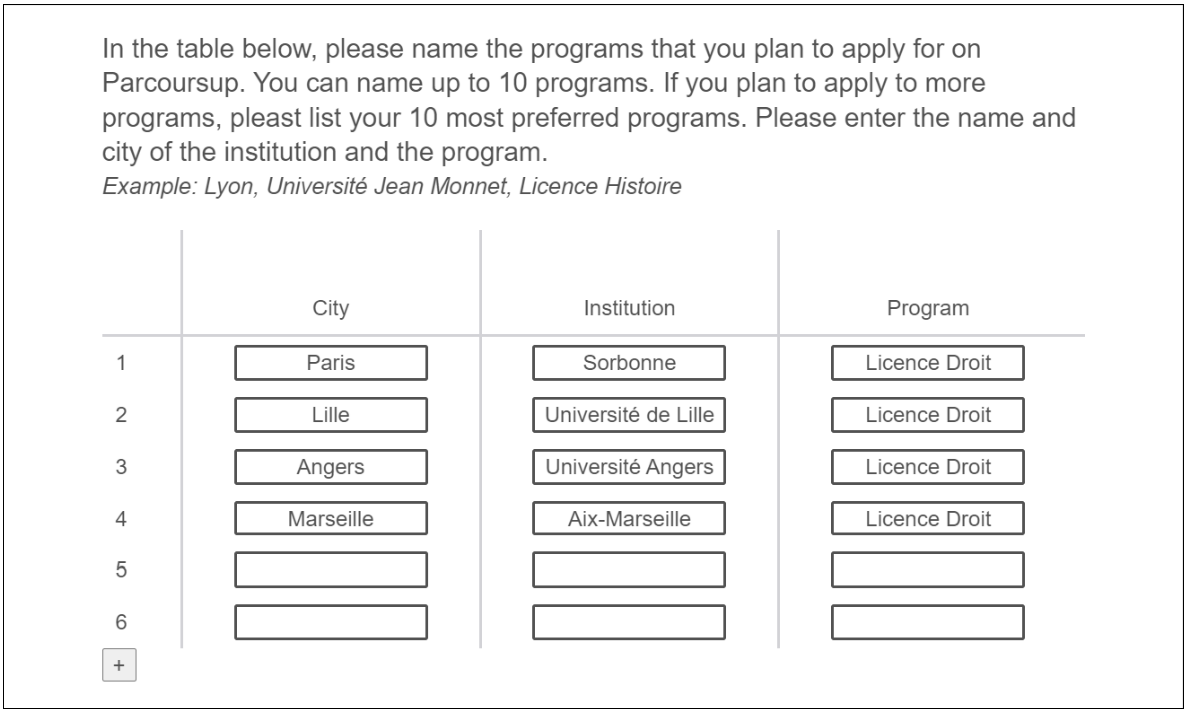
Your contact details may be used to invite you to the follow-up survey on Parcoursup in June and/or September 2021. Your contact details will not be used for other purposes and will be deleted directly after the survey ends (by December 2021 at the latest).

Contact me via eMail

Contact me via SMS

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

Figure G.3: Screenshot of application list elicitation



In the table below, please name the programs that you plan to apply for on Parcoursup. You can name up to 10 programs. If you plan to apply to more programs, pleast list your 10 most preferred programs. Please enter the name and city of the institution and the program.

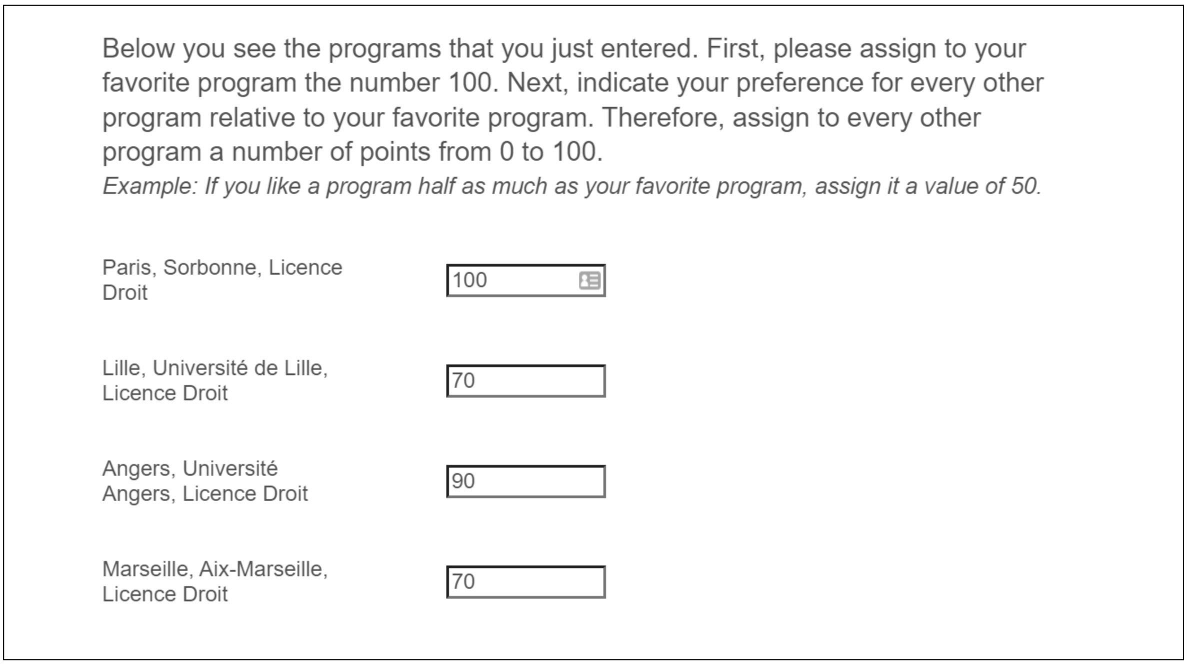
Example: Lyon, Université Jean Monnet, Licence Histoire

	City	Institution	Program
1	Paris	Sorbonne	Licence Droit
2	Lille	Université de Lille	Licence Droit
3	Angers	Université Angers	Licence Droit
4	Marseille	Aix-Marseille	Licence Droit
5			
6			

+

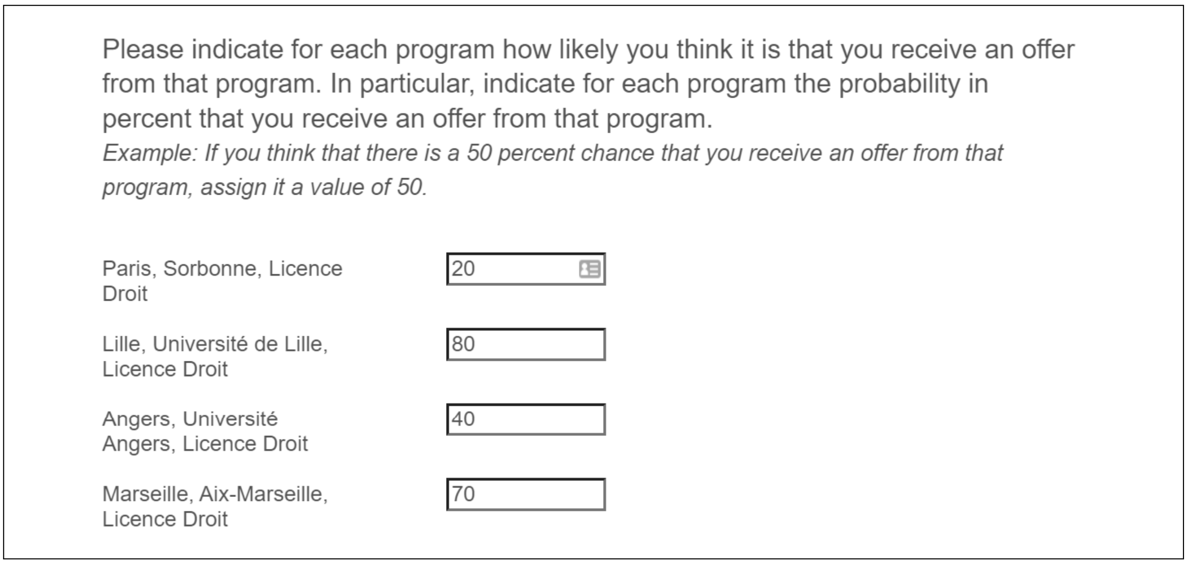
Notes: Subjects were asked to indicate the programs they planned to apply to on Parcoursup. By clicking on [+], they could extend the list and enter a maximum of 10 programs.

Figure G.4: Screenshot of preference elicitation



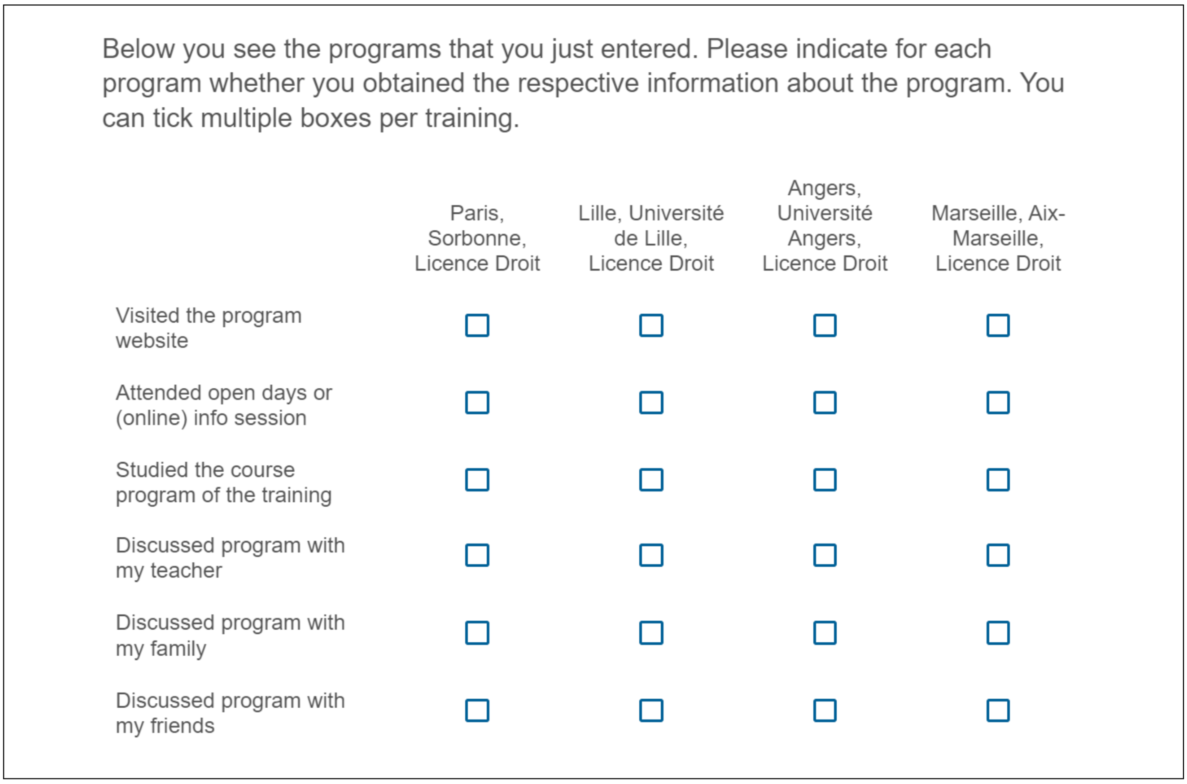
Notes: Subjects were asked for their relative preferences for the programs they had indicated on the previous screen.

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

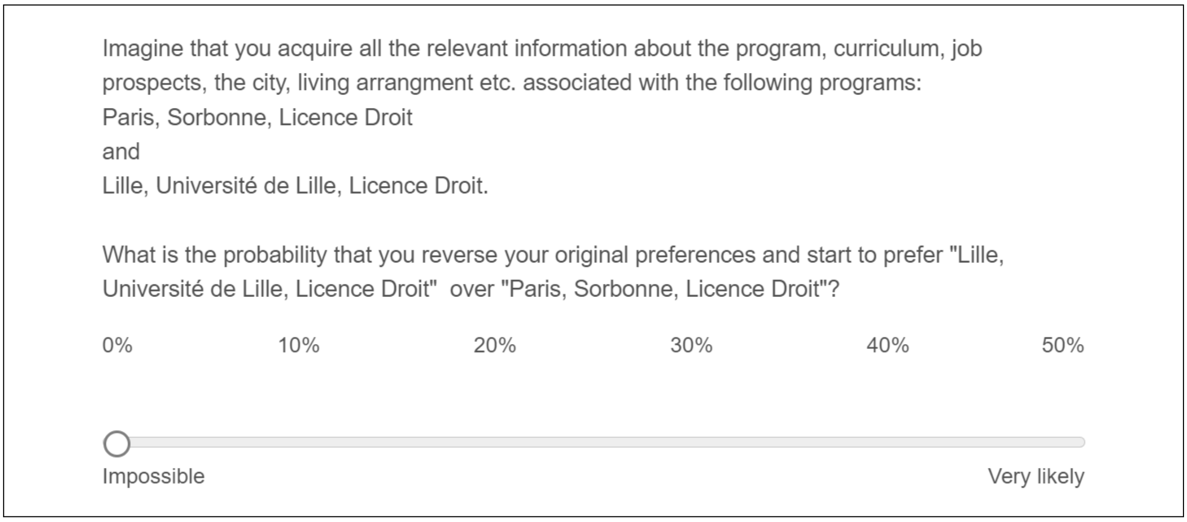


Below you see the programs that you just entered. Please indicate for each program whether you obtained the respective information about the program. You can tick multiple boxes per training.

	Paris, Sorbonne, Licence Droit	Lille, Université de Lille, Licence Droit	Angers, Université Angers, Licence Droit	Marseille, Aix-Marseille, Licence Droit
Visited the program website	☐	☐	☐	☐
Attended open days or (online) info session	☐	☐	☐	☐
Studied the course program of the training	☐	☐	☐	☐
Discussed program with my teacher	☐	☐	☐	☐
Discussed program with my family	☐	☐	☐	☐
Discussed program with my friends	☐	☐	☐	☐

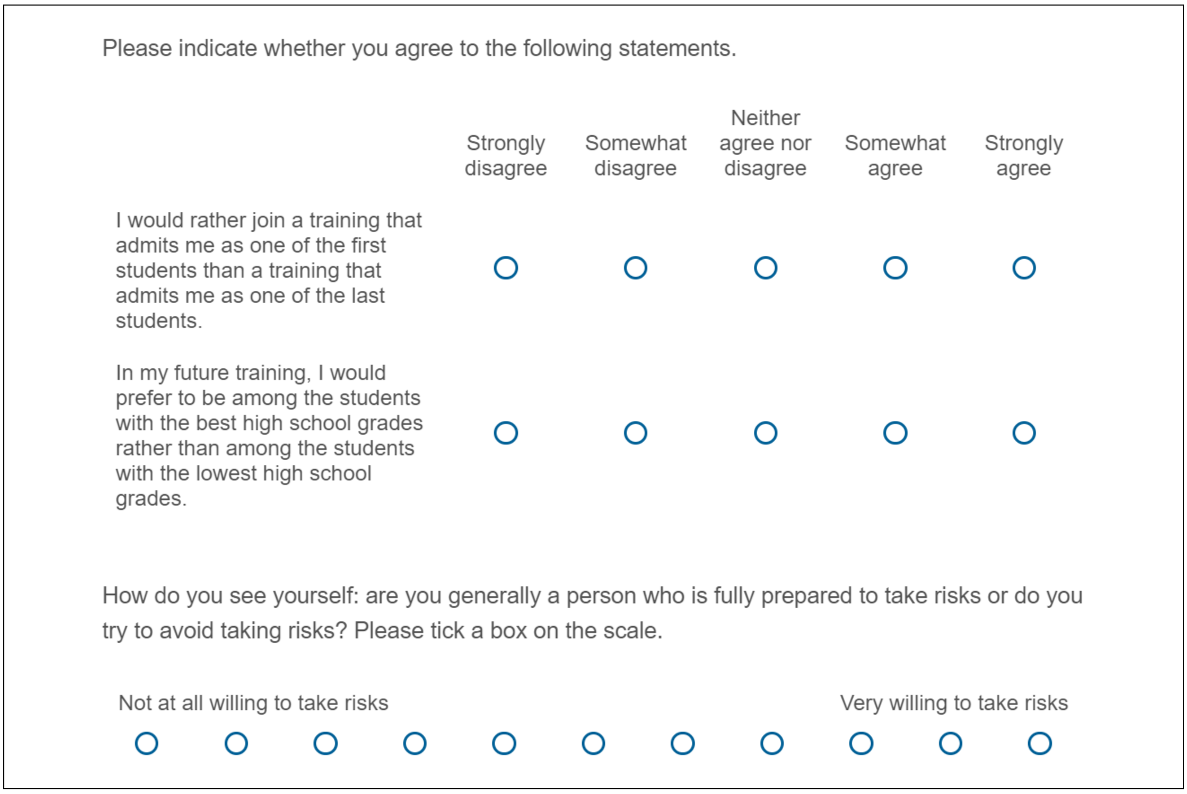
Notes: Subjects were asked whether they had acquired information on the programs they had indicated on the screen in Figure G.3.

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


Please indicate whether you agree to the following statements.

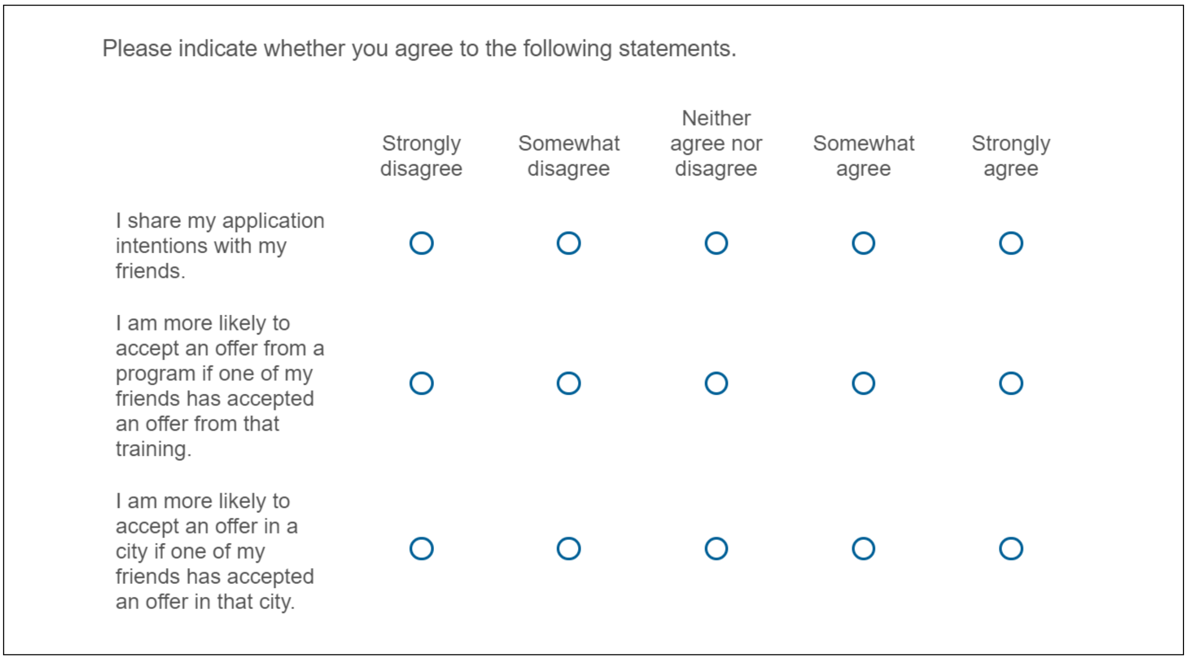
	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I would rather join a training that admits me as one of the first students than a training that admits me as one of the last students.	○	○	○	○	○
In my future training, I would prefer to be among the students with the best high school grades rather than among the students with the lowest high school grades.	○	○	○	○	○

How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale.

Not at all willing to take risks ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ Very willing to take risks

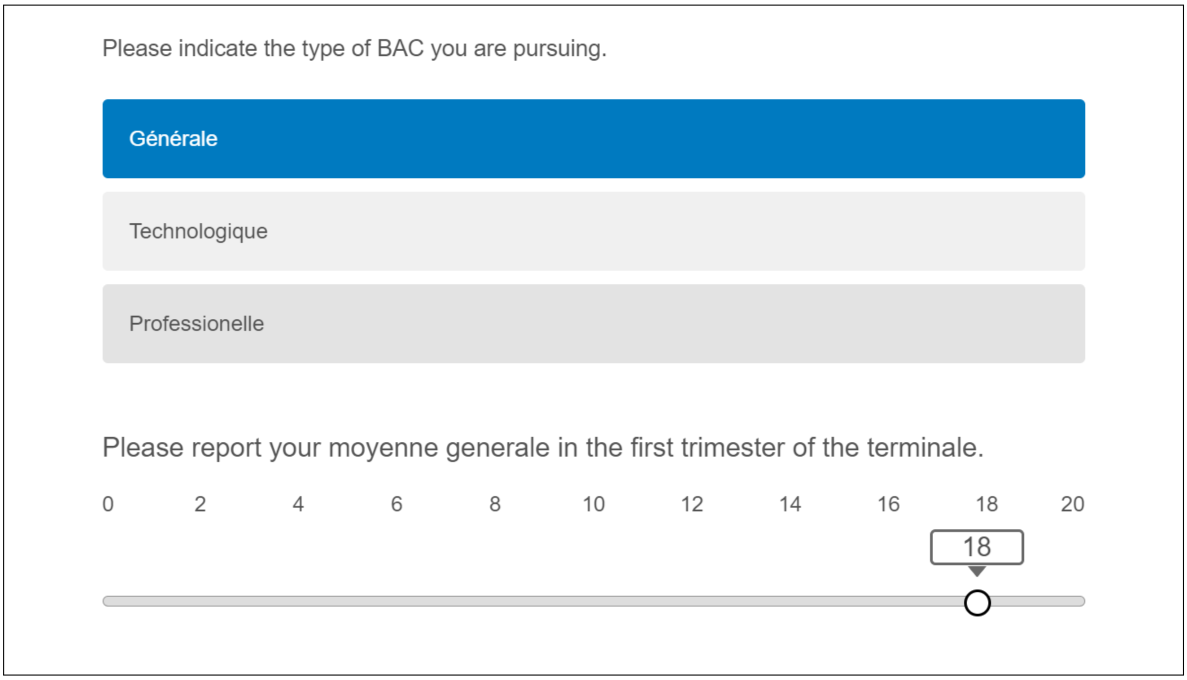
Notes: Subjects were asked for the importance of being among the best students and for their risk preferences.

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



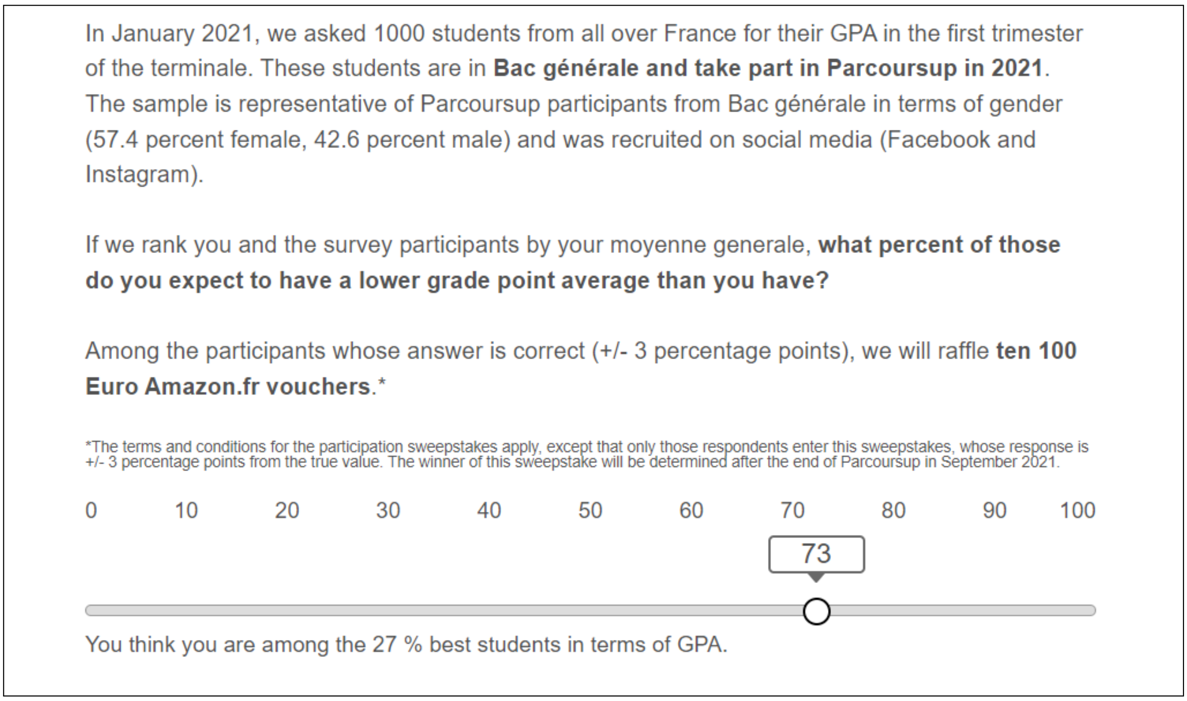
Notes: Subjects were asked whether they had coordinated their applications with their peers.

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



In January 2021, we asked 1000 students from all over France for their GPA in the first trimester of the terminale. These students are in **Bac générale and take part in Parcoursup in 2021**. The sample is representative of Parcoursup participants from Bac générale in terms of gender (57.4 percent female, 42.6 percent male) and was recruited on social media (Facebook and Instagram).

If we rank you and the survey participants by your moyenne generale, **what percent of those do you expect to have a lower grade point average than you have?**

Among the participants whose answer is correct (+/- 3 percentage points), we will raffle **ten 100 Euro Amazon.fr vouchers**.*

*The terms and conditions for the participation sweepstakes apply, except that only those respondents enter this sweepstakes, whose response is +/- 3 percentage points from the true value. The winner of this sweepstake will be determined after the end of Parcoursup in September 2021.

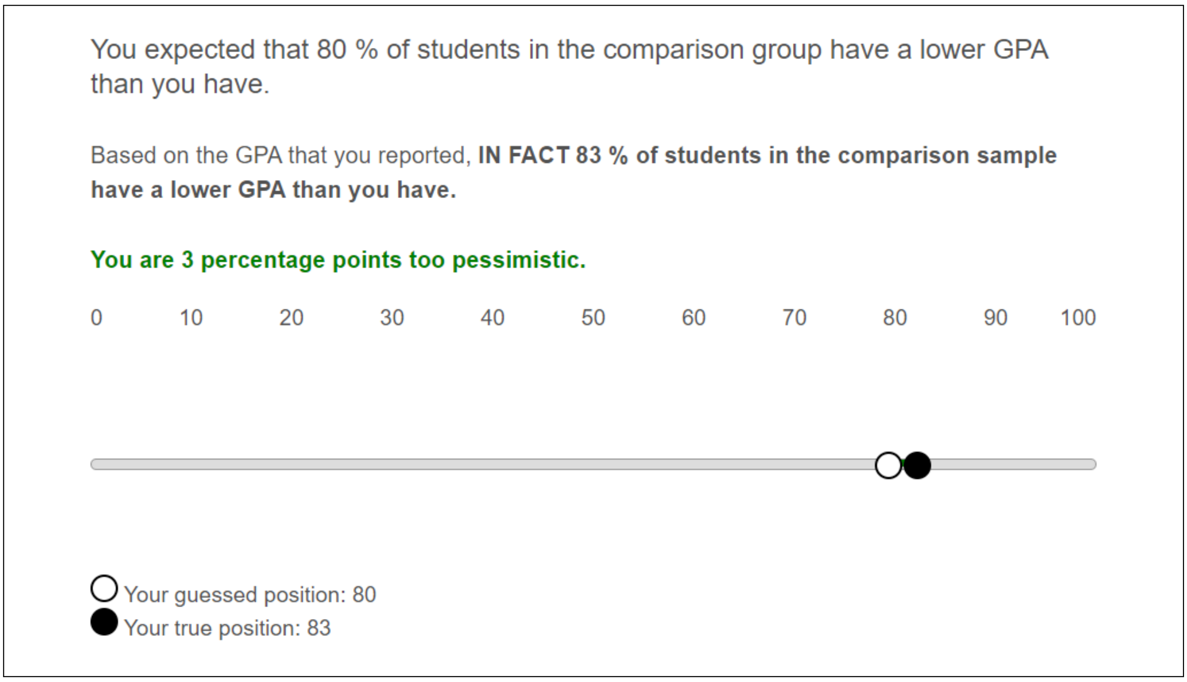
0 10 20 30 40 50 60 70 80 90 100

73

You think you are among the 27 % best students in terms of GPA.

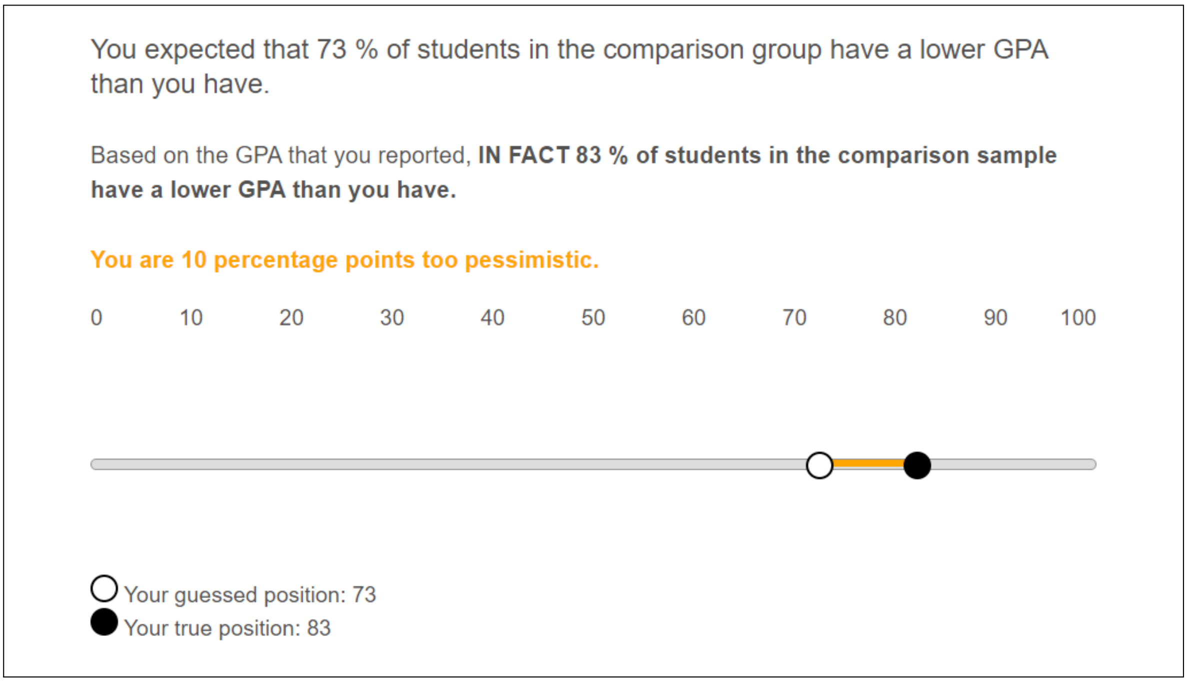
Notes: Subjects were incentivized to guess their rank in the GPA distribution.

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



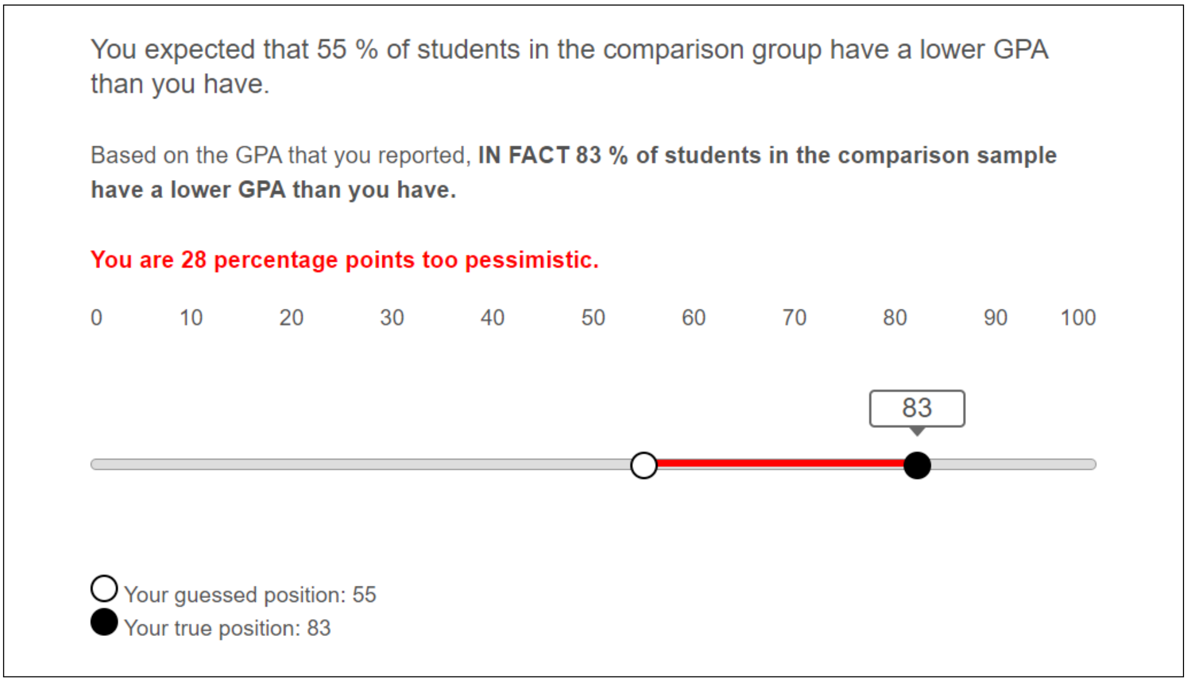
Notes: In this example, the subject underestimated their rank by less than 3 percentiles.

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

Please select the statement that correctly describes the rules of Parcoursup. There is only one correct statement.

Among the participants who give the correct answer, we will raffle **ten 100 Euro Amazon.fr gift cards**.*

By accepting the offer from a program, you renounce to receive any other offers in the furture.

Accepting the offer from a program can reduce your chances of receiving an offer from another program you prefer in the future.

Universities cannot withdraw a tentatively accepted offer, so there is no harm in tentatively accepting an offer and waiting for later offers.

When you receive two offers (or more), you can accept both and wait for future offers to come.

*The terms and conditions for the participation sweepstakes apply, except that only those respondents enter this sweepstakes who give the correct answer. The winner of this sweepstake will be determined after the end of Parcoursup in September 2021.

Notes: Subjects were incentivized to choose the correct statement.

Figure G.16: Screenshot of mechanism knowledge feedback

You did not provide the correct solution.

Explanation

Accepting the offer from a program does not imply that this will be your final choice, nor that you renounce receiving other offers in the future (including offers from programs you may prefer). When you accept an offer while being on the waiting list of other programs, Parcoursup asks you which programs you prefer to the one you accepted. These programs are kept in your preference list.

The correct solution:

Universities cannot withdraw a tentatively accepted offer, so there is no harm in tentatively accepting an offer and waiting for later offers.

Explanation

Universities cannot withdraw an offer they made that has been accepted by a candidate. There is therefore no risk in accepting an offer. In addition, many candidates are on the waiting list of a program they prefer to the one they accepted. **The position on the waiting list can only improve over time.** Indeed, this position improves by one rank every time a candidate rejects an offer from this program. **It is therefore possible that a program you particularly like makes an offer to you very late in the process.** As a result, there is no risk in waiting until the end of the process and observe all offers that you could get. **Patience can only improve your chances of receiving an offer from your preferred program.**

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

Figure G.17: Screenshot of bet on outcome

Please bet on the program that you think you will attend. This means that the program makes you an offer and that you accept that offer.

We will raffle **20 x 50 Euro Amazon.fr gift cards among those respondents for whom the expectation matches the final outcome.***

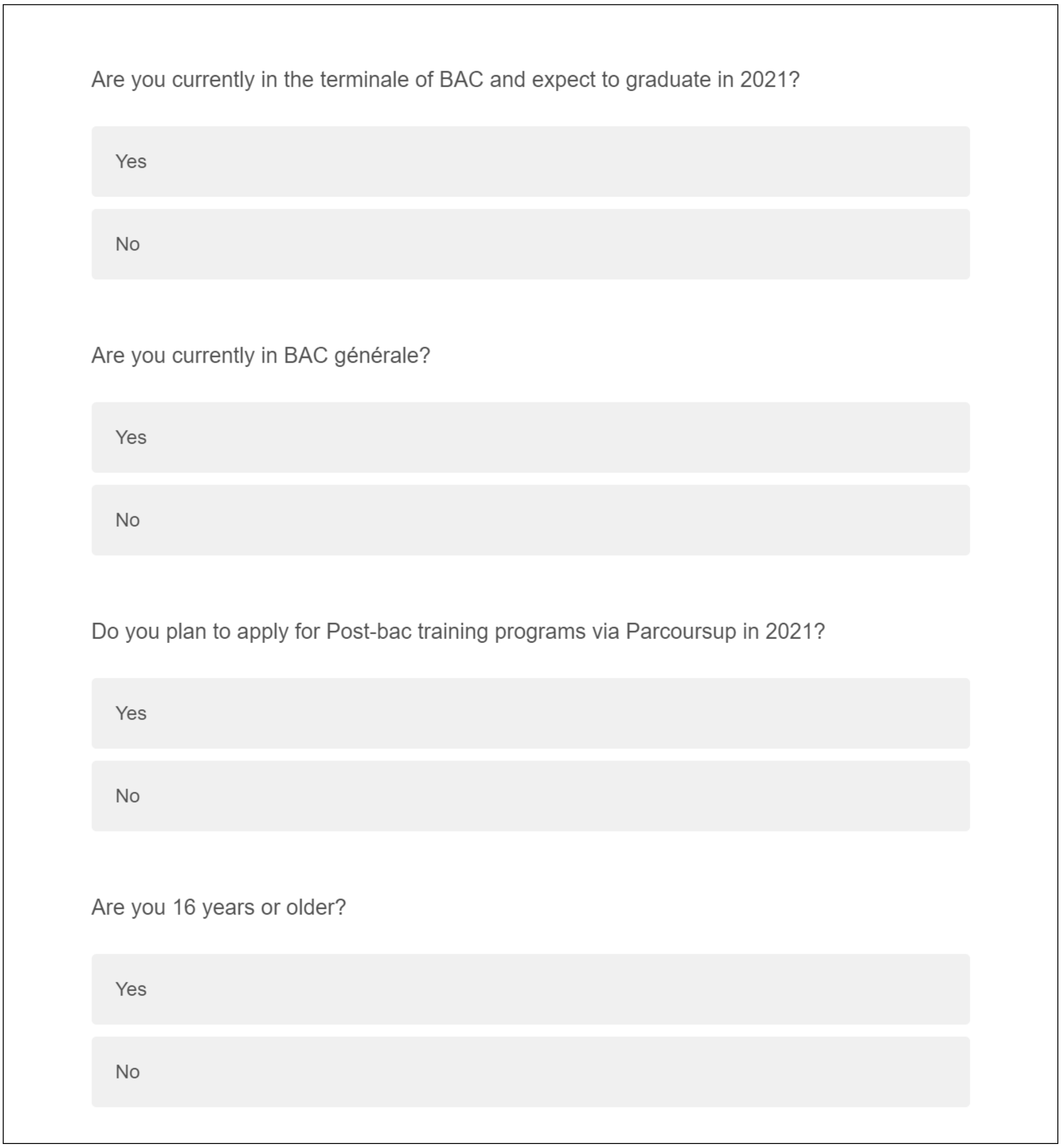
- Paris, Sorbonne, Licence Droit
- Lille, Université de Lille, Licence Droit
- Angers, Université Angers, Licence Droit
- Marseille, Aix-Marseille, Licence Droit

*The terms and conditions for the participation sweepstakes apply, except that only respondents are eligible to win who have predicted their final placement. After Parcoursup has ended (in September 2021), we will draw respondents and ask them to provide proof that they accepted an offer from the training that they predicted (e.g., by sending a screenshot from Parcoursup or a scan of the acceptance letter from the training). Only those respondents who reply within one week and can provide proof of acceptance, will win the gift card. If a person who was drawn cannot provide proof of acceptance or does not reply, we will draw a replacement winner until the 20 gift cards are distributed.

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



Are you currently in the terminale of BAC and expect to graduate in 2021?

Yes

No

Are you currently in BAC générale?

Yes

No

Do you plan to apply for Post-bac training programs via Parcoursup in 2021?

Yes

No

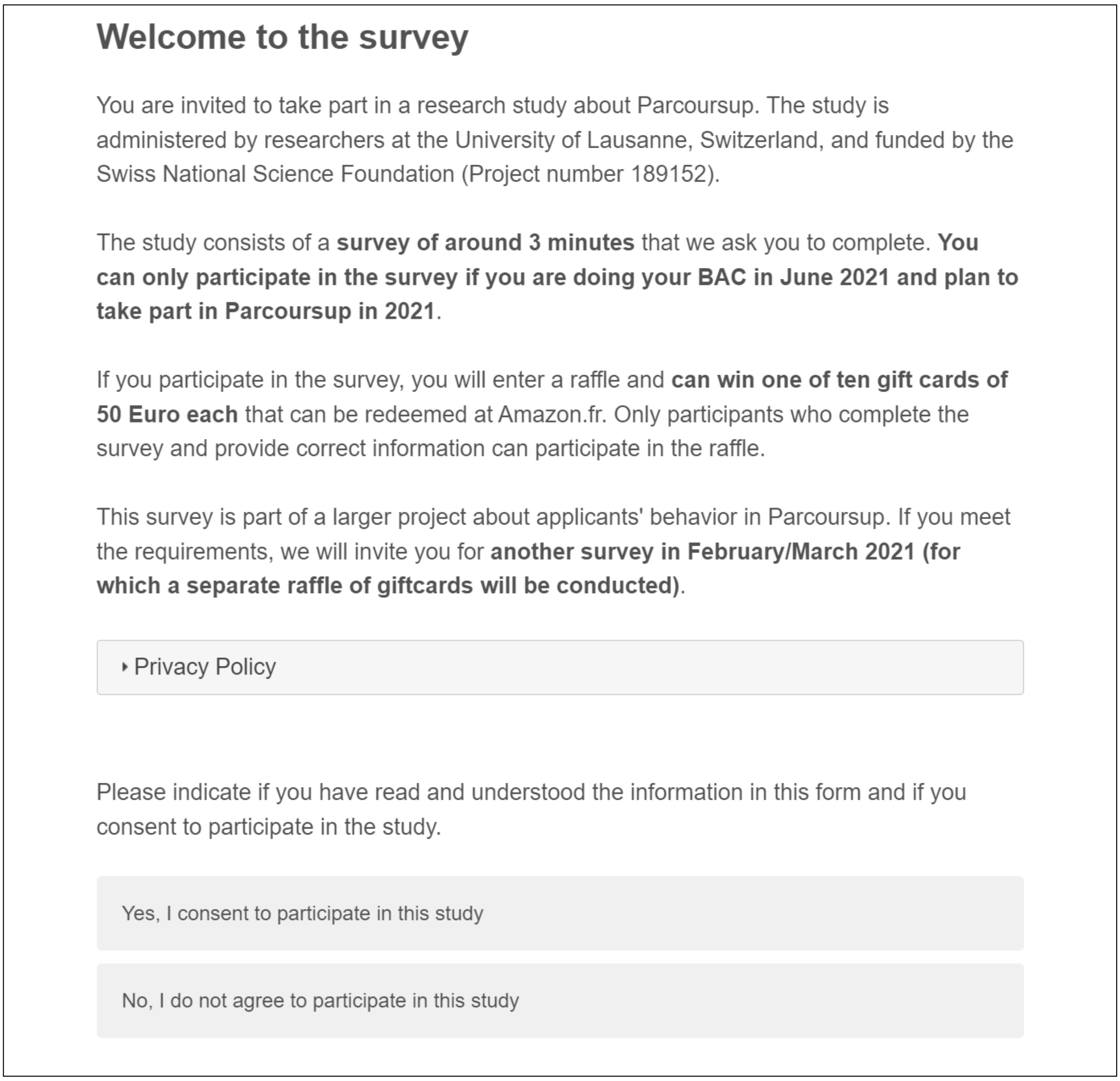
Are you 16 years or older?

Yes

No

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



Welcome to the survey

You are invited to take part in a research study about Parcoursup. The study is administered by researchers at the University of Lausanne, Switzerland, and funded by the Swiss National Science Foundation (Project number 189152).

The study consists of a **survey of around 3 minutes** that we ask you to complete. **You can only participate in the survey if you are doing your BAC in June 2021 and plan to take part in Parcoursup in 2021**.

If you participate in the survey, you will enter a raffle and **can win one of ten gift cards of 50 Euro each** that can be redeemed at Amazon.fr. Only participants who complete the survey and provide correct information can participate in the raffle.

This survey is part of a larger project about applicants' behavior in Parcoursup. If you meet the requirements, we will invite you for **another survey in February/March 2021 (for which a separate raffle of giftcards will be conducted)**.

▸ Privacy Policy

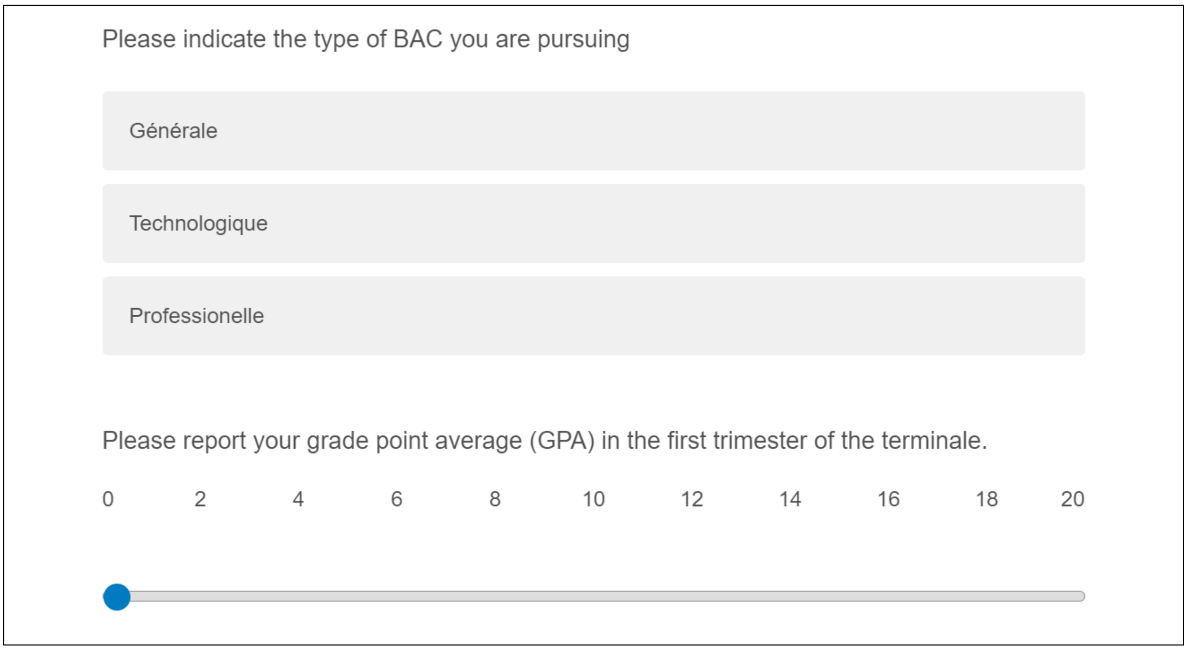
Please indicate if you have read and understood the information in this form and if you consent to participate in the study.

Yes, I consent to participate in this study

No, I do not agree to participate in this study

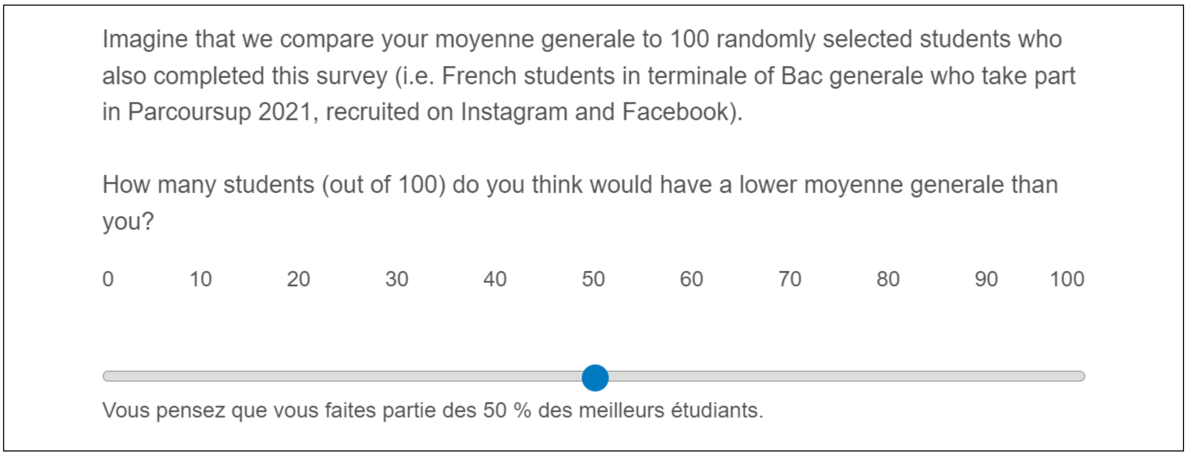
Notes: Subjects are welcomed and asked to consent to the privacy policy. The privacy policy informed participants that their responses would be matched to administrative data and pseudonymized afterwards. On the next screen, they were asked for their demographic details, similar to Figure G.2 below (omitted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

School of Economics and Finance

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