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ABSTRACT

We study a unique grading policy at a large US public university allowing students to mask their letter grades into a "Pass", after having observed their original grade. Using administrative transcript records, we find that female students are substantially less likely to mask their grades than male students, even after accounting for differences in grades, GPA, and course/major taking. We present a framework showing how anticipated discrimination in the labor market can distort incentives to mask across gender. Consistent with the framework, a survey reveals that students anticipate that female students, particularly in STEM, Business, and Economics, will face labor market discrimination which makes them less likely to mask. Our survey allows us to distinguish between anticipated discrimination and other explanations which could contribute to the masking gap, such as preferences for risk or transparency. We find that anticipated discrimination can explain a sizable fraction of the gender gap in masking.

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A large literature documents extensive and persistent labor market outcome differentials between men and women (Blau and Kahn, 2017). In popular discourse, the gender pay gap is often attributed more or less to differential employer treatment towards women (Hill, 2017; Gould et al., 2016). In line with this, evidence from worker surveys indicates high proportions of women reporting having faced gender discrimination in the workplace (Funk and Parker, 2018). Since labor market outcomes are largely determined by pre-market investments like education, a key question is whether women may already anticipate discrimination before they enter the labor market, potentially distorting their education choices and shaping gender inequality.

In this paper, we present evidence that female students expect different returns from signaling their productivity through their grades, specifically because they anticipate labor market discrimination. To do so, we exploit a unique grading policy at a large US public university during the COVID-19 pandemic which allows us to study how male and female students differ in their disclosure of information about their grades. In particular, students were given the option to mask their letter grades into a "Pass" mention excluded from their GPA, after having observed their original grade. Doing so selectively could increase a student's GPA, but introduce uncertainty about how it would be interpreted as a signal of their productivity. Thus, masking decisions provide insights into how students expect their productivity to be assessed in the labor market.

We begin by documenting a gender gap in masking: female students are (economically and statistically) significantly less likely to exercise their option to mask their grades. After accounting for individual differences in grades, GPA, courses, and majors, female students are only 70% as likely to mask a grade as male students. We then present a framework showing how negative stereotypes about female workers in the labor market can distort their incentives to mask grades.[1] More precisely, we outline three channels through which discrimination could distort the masking decision. First, the productivity of female workers could be underestimated, which could be partly overcome by female students signaling their productivity through their GPA. In that case, female students may mask less because they want their GPA signal to be less noisy and therefore receive more weight in the assessment of their produc-

[1] A large literature documents evidence of gender stereotypes in both education and the labor market (Goldin and Rouse, 2000; Reuben et al., 2014; Alan et al., 2017; Bohren et al., 2019; Bordalo et al., 2019; Carlana, 2019; Sarsons, 2017; Breda et al., 2020).

tivity. Second, grades masked by female students may be inferred to be worse than those masked by male students. Third, while not every employer may observe and adjust to a student's masking behavior, individual grades of female applicants may receive additional scrutiny, especially if their GPA goes against established gender stereotypes. As a result, female students may mask less because they are less likely to have their masked GPA taken at face value.

To test these three channels and investigate the role of anticipated discrimination in contributing to the gender masking gap more broadly, we design a survey of perceptions administered to students who had attended the university while the grading policy was in effect. The survey results indicate that students – both male and female – expect that female students would face a larger disadvantage in the labor market if they were to mask. However, female respondents expect anticipated discrimination against females to be much larger. We also find that female students in STEM, Business, or Economics (STEM/BE) are expected to face a larger disadvantage than those in other fields (non-STEM/BE). In particular, we document evidence supporting each of the three proposed channels through which discrimination decreases incentives of female students to mask.

Linking survey responses to administrative transcript records, we directly show that STEM/BE students – but only female students – were less likely to mask when anticipating higher discrimination. Going from the second to the eighth decile of anticipated discrimination for these students leads to a 30% decrease in the likelihood of masking a grade. Overall, controlling for anticipated discrimination closes the masking gap by 22% in STEM/BE and 14% in non-STEM/BE. While we provide suggestive evidence that other factors like risk preferences also contribute to female students masking less, our survey provides explicit evidence of anticipated discrimination, distinguishing it from these other factors. In terms of explanatory power, the role of anticipated discrimination is almost as large as that of risk preferences.

Our findings contribute to several strands of the economics literature. We present evidence that students explicitly account for the impact of their education decisions on their labor market outcomes. More precisely, students expect that their grades, and information about their grades, will be interpreted as a signal of their productivity in the labor market. Substantial work studies how grading systems can affect effort provision and performance. To the extent that these analyses have looked at gender differentials, they have largely focused on differences in preferences, for example regarding risk or competitiveness (Gneezy et al., 2003; Coffman, 2014; Reuben et al., 2014). Our results suggest that the choice of an evaluation system can also create gender differentials by changing how the assessment of students translates into signals of their productivity. Previous work on the economics of education argues that female students put less weight on financial returns and more weight on non-monetary returns when making decisions (Patnaik et al., 2020). Our results suggest that these analyses likely overstate the role of such differences in preferences if female students anticipate their financial returns to be distorted by discrimination.

Previous work on statistical discrimination in the context of race analyzes how discrimination can distort incentives of workers to invest in human capital, namely a college education (Coate and Loury, 1993; Lang and Manove, 2011). Yet, since women account for most college graduates in much of the Western world, gender inequality appears to primarily reflect investment decisions while in college. Our results indicate that the range of education choices distorted by discrimination may be broader than previously understood. Ugalde (2022) documents that female students in male-dominated fields are more sensitive to their early grades than male students when deciding whether to switch away from their major and that some of the difference appears in line with female students expecting differential treatment in the labor market based on their grades. The paper most closely related to ours is Exley et al. (2022), which explores gendered responses to a similar masking policy at a different undergraduate institution. At the writing of this paper, we were not aware of a public version of their paper. However, based on a public abstract (and discussions with the authors), we infer that they find that female students are more likely to reveal negative performance information in STEM. They then conduct field experiments with individuals and employers showing that 1) individuals anticipate discrimination against women in STEM in the absence of information, in line with employer behavior, and 2) individuals expect that providing additional performance information will mitigate discrimination, again in line with employer behavior.

In contrast, by focusing on students, our analysis directly elicits expected discrimination for those impacted by the masking policy, allowing us to establish a direct link between behavior distortion and anticipated discrimination. Students may have inaccurate perceptions about the extent or type of labor market discrimination they would face given a certain signaling decision, but it is still these inaccurate perceptions that affect their behavior and effectively shape labor market outcomes. Accordingly, our results relate to growing evidence that uncertainty and subjective expectations play key roles in determining education decisions as well as resulting economic inequality (Patnaik et al., 2020). Moreover, informed by our theoretical framework, we are also able to provide evidence on specific channels through which discrimination is anticipated.

Thus, our paper is one of few papers that explicitly shows an empirical link between anticipated discrimination and behavior at the individual level. This insight has been used in models of statistical discrimination but, to date, empirical evidence on this has been sparse. Taken together, our findings suggest that mitigating gender inequality may require coordinated efforts targeting both subjective perceptions of discrimination as well as actual discriminatory behavior. Similarly, interventions at different key periods of the life cycle may be necessary, potentially beginning earlier than college when gender stereotypes are shaped and internalized, as well as after labor market entry. Indeed, Cvencek et al. (2011) documents that children express the stereotype that mathematics is for boys, not for girls, as early as in the second grade and that the children applied the stereotype to themselves. Alston (2019) presents evidence that anticipated discrimination can distort the decision of female workers to apply for jobs in male-dominated fields, while Azmat et al. (2020) document that early experiences of workplace discrimination can lead to a gender promotion gap by decreasing aspirations of female workers.

The rest of this paper is organized as follows. In Section 1, we present our analysis of transcript records, investigating gender differentials in masking. Section 2 outlines how anticipated labor-market discrimination can distort masking across gender. Section 3 presents our student survey results, highlighting that female students indeed mask less due to anticipated discrimination. Lastly, Section 4 concludes.

1 Analysis of Administrative Records

1.1 Data

We analyze administrative transcript records from a selective public university in the Midwest. Fall 2020 enrollment consisted of 31,329 on-campus undergraduate students, 50.39 percent of whom were female. On average, first-year students admitted in Fall 2020 had a 3.9 GPA and a 1,490 SAT score.

The student-term-level transcript data provide all courses enrolled in, credits attempted, credits earned, grades obtained, and majors declared. The dataset also provides admission information, including residency, SAT/ACT scores, and demographic characteristics.

During the 2020-2021 academic year, the university had a flexible undergraduate grading policy to alleviate concerns that the COVID-19 pandemic was creating inequitable circumstances for students to pursue their coursework and demonstrate their learning. Specifically, after seeing their final letter grades, students were allowed to mask any grade between A+ and C- into a "Pass" mention.[2] If they masked a grade, they would obtain credits for the course, but the grade would be excluded from their GPA calculation. The policy was announced at the beginning of the year, so students knew they would have the option. The deadline to request a grade conversion was approximately six months after the end of the term. The policy is explained in each student's transcript, so anyone reviewing it, namely employers, would be made aware of the details regarding the "Pass" mention. Key for our purpose, the dataset records not only final grades, but also original grades before masking.

1.2 Descriptive Statistics

There are 57,103 student-term records in Fall 2020 and Winter 2021 and 248,432 student-class records with letter grades from A to C-. Table 1 shows summary statistics by student gender. 22.7 percent of female students masked at least one grade versus 33.2 percent for male students. Female students have a 0.08 higher cumulative GPA, where cumulative GPA is computed prior to the beginning of each term for Fall 2020 and Winter 2021, and 0.068 higher term GPA. They also enroll and earn slightly more credits on average. While our analyses below take this into account by conditioning on the course, major and students' grade distributions, Appendix 1 also provides evidence that the masking policy and COVID-19 pandemic had little overall impact on gender differentials in achievement and course taking.

Conditioning on students who masked at least one grade, female students masked fewer grades on average at 1.46 versus 1.65. Masking allowed students to increase their term GPA substantially, by 0.36-0.38 on average.

Incentives to mask a grade should be lower for better grades. As shown in Figure

[2] Students who received D+, D, D-, or E grades received no course credit and a "No Record Covid" (NRC) grade which did not affect their GPA.

1, the likelihood of masking a grade is much higher for grades far below a student's GPA and nearly falls to 0 for grades above. Indeed, around 97% of the 24,849 grade masking requests increase the student's cumulative GPA once masked. Figure 2(a) shows that a grade of B+ is less than 20% likely to be masked compared to over 70% for C-. Throughout the grade distribution, female students are less likely to mask. Moreover, Figure 2(b) shows masking propensities based on cumulative GPA as of Winter 2020 (the semester before the grading policy came into effect), indicating that students in the middle of the GPA distribution are more likely to mask grades. On one hand, students with a very low cumulative GPA heading into Fall 2020 are less likely to benefit substantively from masking if they also obtain low grades in that term. On the other hand, students with a very high GPA are likely to also obtain high grades in Fall 2020 which they have little incentive to mask. Again, we see that female students are significantly less likely to mask grades throughout the distribution of cumulative GPA (except in cases where the cumulative GPA is 2.5 or less).

1.3 Empirical Analysis

We now turn to a formal analysis of the propensity to mask course grades across gender using data from the Fall 2020 and Winter 2021 semesters. We first explore differences in the probability of a student masking at least one of their grades using a logit model. The estimating equation can be written as follows:

$$y_i^* = \alpha_0 + \alpha_1 Female_i + \alpha_2 X_i + FE_{major} + \epsilon_i \tag{1}$$

$$Y_i = \begin{cases} 1 & if \quad y_i^* > 0 \\ 0 & otherwise, \end{cases}$$

where i denotes a student, X_i student characteristics including cumulative GPA prior to the start of each term and number of courses taken each term, and ϵ_i is an error term.[3] The dependent variable Y_i is a binary variable taking the value one if student i has masked at least one grade. $Female_i$ is an indicator for female students and

[3] We compute cumulative GPA prior to the beginning of each term in which students could mask grades. We do not include the current term's GPA in our calculation since it could be affected by the masking policy. The cumulative GPA of a student as of Fall 2020 could include grades masked in Winter 2020, but it is taken as given by the student for Fall 2020 and is therefore the relevant GPA measure to capture masking incentives for the current term.

$\exp(\alpha_1) = \frac{P_F(Y_i=1|X_i)/P_F(Y_i=0|X_i)}{P_M(Y_i=1|X_i)/P_M(Y_i=0|X_i)}$ is the parameter of interest capturing the female-to-male masking odds ratio.

These results are shown in Table 2. Column (1) shows that female students are only 59% as likely as male students to have masked at least one grade, without controls. Controlling for student characteristics (cumulative GPA, number of courses, number of letter-graded courses, number of core courses, average course difficulty,[4] mean and standard deviation of term grades),[5] Column (2) shows that female students are still only 64% as likely to have masked as male students. In Column (3), adding major fixed effects further reduces the gap, but it remains sizable as female students are still estimated to only be 75% as likely as male students to have masked.

We next analyze the number of grades masked by students, conditional on having masked at least one:

$$Y_i = \alpha_0 + \alpha_1 Female_i + \alpha_2 X_i + FE_{major} + \epsilon_i,$$

where Y_i is the number of grades masked (≥ 1) and α_1 is the parameter of interest. Columns (4)-(6) of Table 2 show these results. Without any controls, female students who mask at least on grade mask 0.19 fewer course grades (that is, 12 percent fewer than males). Controlling for student characteristics and major fixed effects in Column (5) and (6) sequentially, female students still mask 7 percent and 6 percent fewer courses than their male counterparts. While there is a gender masking gap at both the intensive and extensive margins, it appears smaller at the extensive margin since, among students who mask, most (62%) mask only one grade.

Next, we analyze masking at the student-grade level to investigate gender differentials that arise even within a given course. We augment equation (1) to include the original grade obtained for the course. Table 3 shows the results. Column (1) reports that female students are only 55% as likely to mask a grade, without controls. Column (2) controls for the course grade; column (3), in addition, controls for cumulative GPA, course difficulty, number of courses taken, number of letter-graded courses, the

[4]We consider two alternative measures for course difficulty which leave our results unchanged, both qualitatively and quantitatively. First, we consider the average GPA of students taking the course in the last 5 years. Second, we consider the average SAT of students taking the course in the last 5 years. See Table A5.4.

[5]We control for the mean and standard deviation of term grades since they affect incentives to mask. Even holding cumulative GPA constant, a student is less likely to mask one of their grades in the current term if their grades are better on average. Similarly, a student with two Bs has the same average grade as one with an A and a C, but the latter could benefit more from masking (their C).

standard deviation of term grades, and an indicator for whether the course is a core course. Adding these controls has little qualitative impact on the odds-ratio. Finally, column (4) adds major fixed effects, indicating that female students are still only 69% as likely as male students to mask, holding everything else constant.

In Appendix 5, we conduct robustness checks and heterogeneity analyses. First, we use a Linear Probability Model (LPM) which allows us to add individual course fixed effects. Second, we show that the gender masking gap is present for both first and fourth year students, but is substantially larger for the latter group. Third, we show that the gender masking gap is also present when restricting only to core courses, which may be more important indicators of a student's performance in a field.

Overall, we find robust evidence that, after accounting for differences in grades, majors, and course-taking, female students were less likely to mask their grades. To gather evidence on whether this result was easy to anticipate given previous work on gender differences in economics, we conducted a survey of 73 experts, over 47% of whom reported directly having worked on gender-related topics, sampling from labor and education economics faculty in North America and Western Europe. The results shown in Table 4 indicate that only 18% of respondents reported that female students would be less likely to mask than male students, holding constant the grade, GPA, course, and major. This highlights how considering education choices as signals of productivity for the labor market yields novel insights for our understanding of gender differences that have been missing from much of the literature. Next, we propose a theoretical framework in which female students expect lower returns from masking when they anticipate labor-market discrimination.

2 Theoretical Framework

In this section, we present a simple framework illustrating how anticipated discrimination in the labor market can lower incentives of female students to mask. Students consider their grades as a signal of their productivity for the labor market and masking distorts this signal. In particular, we outline three channels through which female students may anticipate their grades or masking behavior to be treated differently than that of male students.

A student observes their grade g_c for course c worth C_c credits and decides whether to mask it into a pass $m_{g_c} = 1$ or not $m_{g_c} = 0$. The benefit of masking grade g_c is that it no longer counts in the student's GPA calculation, potentially increasing their GPA. In particular, the difference in GPA from masking g_c corresponds to:

$$GPA_{m_{g_c}} - GPA = GPA_{g_1,\ldots,g_{c-1},g_{c+1},\ldots,g_N} - GPA_{g_1,\ldots,g_N} = \frac{[GPA_{g_1,\ldots,g_{c-1},g_{c+1},\ldots,g_N} - g_c]C_c}{\Sigma_{n=1}^{N} C_n}. \tag{2}$$

A student's GPA represents a signal of productivity for the labor market. In the absence of masking, employers estimate a student's productivity P from their GPA, $GPA = P + \varepsilon$ with $\varepsilon \sim N(0, \sigma_\varepsilon^2)$, as well as a direct signal of productivity, $s = P + \mu$ with $\mu \sim N(0, \sigma_\mu^2)$, for example from an interview. A student's expected productivity then corresponds to:

$$E[P|GPA, s] = \gamma GPA + (1-\gamma)s \text{ with } \gamma = \frac{\sigma_\mu^2}{\sigma_\varepsilon^2 + \sigma_\mu^2}. \tag{3}$$

Unlike in signaling models where agents engage in costly investments to alter the information they convey, students face no direct cost of masking a grade to alter their GPA signal. Rather, potential costs of masking arise from affecting labor market outcomes by influencing employer perceptions. First, masking a grade decreases the GPA signal's precision since it introduces uncertainty about the masked grade, leading employers to potentially put less weight on the GPA in their evaluation of the student. Second, masking can introduce uncertainty about the GPA signal itself if employers attempt to infer a student's masked grades, for example from their other grades or characteristics. Third, in some cases, employers may be unaware of a student's masking if they only rely on an aggregate GPA signal without looking at individual grades. In other cases, employers may adjust a student's GPA based on their inference of the student's masking, $\hat{GPA}$.[6]

[6]If employers always adjusted a student's masked GPA, if $\hat{GPA} = GPA$ on average, and if students only masked grades that would otherwise lower their GPA, then the only equilibrium inference would be that masked grades correspond to the lowest passing grade, at which point students would expect no benefit from masking even those grades. Otherwise, students would mask if and only if $\hat{GPA} > GPA$. Accordingly, while only masking grades that would individually lower the unmasked GPA is not necessarily an optimal strategy for students, over 97% of masked grades satisfy this condition in our data. To capture the fact that students mask, but not all of them and not all of their below-average grades, we consider the potential that students expect some employers to not adjust to their masking or to do so incorrectly, consistent with a large literature on rational

The model focuses on how discrimination can distort incentives to mask by changing employers' inference of a student's expected productivity. Nevertheless, increasing variance and uncertainty of the GPA signal could also have indirect costs like a mismatch between the student's qualifications and the job requirements, additional variance in the student's labor market outcomes, or if students have a preference for transparency. Let $T(\mathbb{1}(m_{g_c} = 1))$ represent this type of costs from masking. Since these factors can be difficult to investigate empirically, the student survey presented below helps us distinguish between anticipated discrimination and potential components in $T(\cdot)$.

Assuming employers take the student's masked GPA as their unmasked one with probability p, and otherwise correctly infer the unmasked GPA from the masked one on average, $G\hat{P}A = GPA + \eta$ with $\eta \sim N(0, \mathbb{1}(m_{g_c} = 1)\sigma_\eta^2)$. Letting g_c correspond to a student's worst grade for the term, the student maximizes the following objective function choosing whether to mask g_c or not:[7]

$$
\begin{aligned}
&E[P|GPA, s] - T(\mathbb{1}(m_{g_c} = 1)) = \\
&p[\gamma GPA_{m_{g_c}} + (1-\gamma)s] + (1-p)[\gamma_m GPA + (1-\gamma_m)s] - T(\mathbb{1}(m_{g_c} = 1))
\end{aligned}
\tag{4}
$$

where $\gamma_m = \frac{\sigma_\mu^2}{\sigma_\varepsilon^2 + \mathbb{1}(m_{g_c}=1)\sigma_\eta^2 + \sigma_\mu^2}$.

2.1 Anticipated Discrimination and Masking

Assume that students are divided into two groups $d = \{F, M\}$. Holding grades, courses and major constant, we propose that gender differences in masking could arise from anticipated discrimination in the labor market through three channels.

First, if employers generally underestimate the productivity of female students, then female students may benefit from employers putting as much weight as possible on their GPA signal, decreasing their incentives to mask. Second, employers' inferences about masked grades of female students could differ, such that a male and

inattention (Maćkowiak et al., 2021).

[7] Under the assumption that students only mask grades which would otherwise lower their GPA, we can consider the decision to mask each grade sequentially starting from the student's lowest grade for the term.

female student with identical masked GPAs may be expected to hold different unmasked GPAs. Third, employers may give additional scrutiny to profiles of female students, especially if they conflict with established stereotypes, consistent with confirmation bias or attention discrimination (Bartoš et al., 2016). We now present an overview of each channel.

2.1.1 Underestimation of Productivity

Employers predict a student's productivity from their GPA and a direct signal, for example from an interview. In the absence of masking, a student's GPA is a comparatively objective and standardized performance measure. Accordingly, negative group perceptions are likely to enter an employer's assessment through their direct signal. If employers systematically underestimate the productivity of female students from this direct signal, then female students can be encouraged to not mask so that employers put more weight on their GPA when assessing their productivity.

In particular, assume $s_d = P - B\mathbb{1}(d = F) + \mu$ where B is a positive constant capturing negative employer perceptions. Students do not observe s, but form an expectation over it. $E[s_d] = GPA - B$ for female students and $E[s_d] = GPA$ for male students. Contrast the inferred productivity of a female student with and without masking:

$$p[\gamma GPA_m + (1-\gamma)E[s_F]] + (1-p)[\gamma_m GPA + (1-\gamma_m)E[s_F]] \tag{5}$$

and

$$\gamma GPA + (1-\gamma)E[s_F]. \tag{6}$$

For a large enough bias ($B > \frac{p\gamma(GPA_M - GPA)}{(1-p)(\gamma-\gamma_m)}$), it is optimal for the student not to mask her grade. In contrast, it is easy to verify that male students weakly prefer to mask (abstracting from $T(\cdot)$).

2.1.2 Underestimation of Masked Grades

The introduction of the masking policy was new and unique, likely leaving employers with little experience inferring from masked grades. If employers hold negative stereotypes about the productivity of women, they may infer, holding other grades constant, that a grade masked by a female student is worse on average. The key distinction with the first mechanism is that gender stereotypes in this case directly affect how signals are interpreted, with implications for policies designed to mitigate group disparities through the provision of additional information.

Assume $G\hat{P}A_g = GPA - B\mathbb{1}(g = F) + \eta$ where B is again a positive constant capturing negative employer perceptions. Also assume $E[s_F] = E[s] = GPA$ for both male and female students. Contrast the inferred productivity of a female student with and without masking:

$$p[\gamma GPA_m + (1-\gamma)E[s]] + (1-p)[\gamma_m E[G\hat{P}A_g] + (1-\gamma_m)E[s]] \tag{7}$$

and

$$\gamma GPA + (1-\gamma)E[s]. \tag{8}$$

For a large enough bias ($B > \frac{p\gamma(GPA_M - GPA)}{(1-p)\gamma_m}$), it is optimal for the student not to mask her grade. In contrast, a male student facing $B = 0$ again weakly prefers to mask (abstracting from $T(\cdot)$).

2.1.3 Additional Scrutiny from Employers

Previous work has found that the extent to which agents seek additional information when making a decision depends on whether their current information tends to confirm or contradict their prior. Given a male and a female student with an identical masked GPA, if employers expect female students to be less productive on average or set particularly strict requirements for female applicants, then they may be more likely to investigate their individual grades and adjust their GPA signal, decreasing incentives to mask.

Assume $p_F < p_M$ and $E[s_g] = GPA$ from the perspective of both female and male students. Incentives to mask are increasing in p_g, as seen from the derivative of equation (3) with respect to p:

$$\gamma(GPA_m - GPA), \tag{9}$$

which is positive when students mask grades in order to increase their GPA. As a result, female students have lower incentives to mask.

3 Student survey

3.1 Design

To test the framework's predictions and distinguish the role of anticipated discrimination from other potential factors contributing to the gender masking gap, we fielded a student survey early in Fall 2022. This online survey was administered on Qualtrics and sent to a random sample of juniors and seniors who were exposed to the masking policy. The first 300 respondents who completed the survey were guaranteed to receive a $10 Amazon gift card. The remaining students who completed the survey were eligible for a random drawing of 1 of 100 $10 Amazon gift cards.

A total of 631 students completed the survey, 58% of whom were female, corresponding to a response rate of approximately 10%. Appendix 2 compares the survey sample to the transcript data. The survey includes a higher fraction of female, STEM/BE, lower-income, and high-achieving students. Masking behavior is similar across the survey sample and student population.

Throughout the survey, we asked beliefs about anticipated discrimination in STEM/BE and non-STEM/BE separately given substantial evidence of negative gender stereotypes in STEM and economics (Reuben et al., 2014).

For some survey questions, we asked students their beliefs (first-order) as well as their beliefs about the beliefs of other students (second-order). For example, one survey question asked "Considering students in the following groups [STEM/BE female, STEM/BE male, non-STEM/BE female, or non-STEM/BE male] who masked at least one grade, what do you think their original grade on that course would have been (on average)?" for first-order beliefs, followed by "How do you think your peers (other students) answered this question?" for second-order beliefs. We use second-order beliefs as an approximation of expected beliefs in the labor market. We use this approximation rather than asking students their beliefs about employers, because it allows us to incentivize belief elicitation. Namely, for each of 6 survey questions about second-order beliefs (3 question types asked separately for students in STEM/BE and non-STEM/BE), students received \$0.25 if they reported beliefs sufficiently close to the true belief distribution of their peers.

Beyond questions informed by our theoretical framework, we included questions about risk preferences, attitudes towards grades, and knowledge of the policy in order to investigate other potential factors contributing to the masking gap. See Appendix 6 for the survey questionnaire.

3.2 Results

We now present survey evidence that female students are expected to face labor market discrimination consistent with decreasing their incentives to mask. In what follows, we pool answers from male and female respondents as well as views regarding both STEM/BE and non-STEM/BE together. Appendix 4 presents the survey results split by respondent gender and views regarding STEM/BE and non-STEM/BE.

We begin by documenting that female students are expected to face a clear disadvantage at the hiring stage in Figure 3. Given equal qualifications and no masked grades, 68% of students reported that an employer would make an offer to a male applicant over a female applicant (this percentage is similar for the case in which both students mask). This number increases to 85% when the female applicant masks but the male applicant does not, and decreases to 26% if the male masks but the female does not. This pattern reveals two insights. First, students expect that the decision to mask, at the margin, is important in determining which applicant gets an offer. Whatever baseline disadvantage students expect female applicants to face, it is overturned if the male applicant masks and the female applicant does not. Second, a male applicant who masks still retains an advantage over a female applicant who masks, holding constant the other applicant's behavior. Indeed, if the female applicant masks, 85% of students reported that the male candidate would receive the offer, but only 74% of students reported that the female candidate would receive the offer in the opposite scenario.

Figure 4 presents evidence that students expect the average GPA of female students to be underestimated compared to that of male students. Indeed, respondents believe that male students have a 3.40 average GPA and that their peers would report approximately the same value. In contrast, they believe that female students have a 3.48 average GPA but that their peers would report that female students only have a 3.42 average GPA. Accordingly, students expect their peers to underestimate the GPA of female students by around 15% of a standard deviation or 85% of the true GPA difference between female and male students. We take this as an indication that the GPA of women, and therefore their productivity, is believed to be underestimated in the labor market. In the context of the model's first channel, this gives an incentive for female students to avoid masking, such that employers put more weight on their GPA signal, which on average will be a positive shock.

Figure 5 presents evidence that students expect grades masked by female students to be inferred as lower than they were, and that this difference is larger than for male students. Indeed, respondents believe female students masked a 3.14 grade on average, but that their peers would report that female students masked a grade of only 3.05 on average. This difference is expected to be less than half as large for grades masked by male students. Consistent with the model's second channel, a female student with identical grades as a male student will be inferred to have a lower unmasked GPA if both students mask a grade, disincentivizing female students from masking.

While beliefs determine masking behavior, whether they are correct or not, it is interesting to compare beliefs to the true average GPA and average masked grade across gender. Appendix 3 shows that students systematically underestimate the average GPA of both male and female students but overestimate their average masked grade, and that these prediction mistakes are more pronounced for male respondents.

Figure 6 presents evidence that students expect employers to be more likely to look at individual grades of female than male applicants (38.3% versus 35.3%; p-value of the difference is 0.000) rather than relying on their GPA alone. While increased attention on a student's profile is not necessarily negative, in the context of the model, female students' masked grades are less likely to go unnoticed which decreases their expected benefit from masking. Moreover, this anticipated attention seems unlikely to reflect an advantage in hiring given evidence from Figure 3.

Appendix 4 shows that both male and female students expect female students to be disadvantaged at hiring, have their GPA underestimated, have their masked grades underestimated, and face additional scrutiny at hiring, but that female students expect these differentials to be substantially larger.

Overall, our survey results support the proposition that anticipated discrimination distorts incentives for female students to mask. Given that gender stereotypes have often been associated with STEM/BE fields, it is also useful to summarize and compare anticipated discrimination across major types. First, Appendix 4 presents graphical evidence separating views of respondents about students in STEM/BE versus non-STEM/BE and showing that anticipated discrimination against female students appears higher in the former.

Next, we build a discrimination index by averaging answers on the main survey questions shown in the previous section.[8] The index gives us a summary measure of subjective views about discrimination faced by female students in STEM/BE or non-STEM/BE majors, *relative* to male students in those fields.

Table 5 summarizes the index across respondent types and views regarding female students in STEM/BE and non-STEM/BE. Qualitatively, respondents anticipate that female students face discrimination across the board, as indicated by the positive index value. Interestingly, anticipated discrimination against female students is over twice as high in STEM/BE fields, whether reporting views across all respondents or respondents in their own field. Comparing rows 1 and 2 also indicates that non-STEM/BE students expect female STEM/BE students to face higher discrimination than STEM/BE students themselves expect them to (this is not the case for non-STEM/BE). Lastly, in both fields, anticipated discrimination against female students is reported to be much larger by female respondents.

We then link survey respondents to our transcript data to test whether anticipated discrimination helps predict the decision to mask at the individual level. Figure 7 separates the discrimination index in 10 deciles and shows the relationship between the likelihood of masking and the discrimination index, controlling for the student's GPA and their grade in a course as well as major fixed effects and other standard controls. The first panel shows that female students in STEM/BE who anticipate that female students in STEM/BE face higher discrimination are less likely to mask

[8]In particular, our discrimination index is the sum of three -1/1 variables capturing whether a respondent anticipates discrimination against female students relating to their average GPA, their masked grades, and whether they believe that a male candidate would receive the employment offer when both genders mask a grade. Anticipated discrimination against female students relating to average GPA/masked grade = 1 if $FO_F - SO_F - (FO_M - SO_M) > 0$. FO_F and SO_F (FO_M and SO_M) stand for first-order and second-order beliefs of respondents about the average GPA/average masked grade of female (male) students. Anticipated discrimination against female students in employment = 1 if a male candidate would receive the offer when both genders mask a grade. The index is computed separately for views about students in STEM/BE and non-STEM/BE. Corresponding survey questions are described in Figures 3, 4 and 5. The index ranges from -3 to 3.

their grade. Precision is diminished in this restricted sample, but the estimated magnitude is substantial - going from the second to the eighth decile of anticipated discrimination is associated with a 30% decrease in the probability of masking a grade. In contrast, the decision of male students to mask is largely unaffected by their views on expected discrimination, either against female or male students (the discrimination index against male students is simply -1 times that against female students). As shown in the second panel, the decision of students, both female and male, to mask in non-STEM/BE fields is also seemingly unaffected by anticipated discrimination in those fields.

Table 6 reports similar results in the form of odd ratios from a logit regression. It also compares the impact of anticipated discrimination on the masking gap to that of risk preferences, a well-documented driver of gender differences in the literature. In the survey, we asked students: "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please select a number between 1 and 7 where 1 means 'absolutely unwilling to take risks' and 7 means 'fully prepared to take risks'." Female students, especially in STEM/BE, reported being much more risk-averse than male students (see Table 7). Moreover, we find that adding risk preferences and anticipated discrimination closes 59% of the gender masking gap in STEM/BE, from 0.76 to 0.90, with anticipated discrimination itself closing the gap by 22%. Column (4) shows that the discrimination index is a statistically significant determinant of the masking decision for female students only. Moving to columns (5)-(8) of Table 6, we see that in non-STEM/BE, anticipated discrimination still explains 14% of the gender masking gap. However, similarly to Figure 7, the relationship with masking is not statistically significant for either gender.

Table 7 presents evidence on other factors unrelated to discrimination which could help explain the masking gap. To be clear, factors like preferences for risk or transparency may contribute to the masking gap, but they do not constitute confounders for the specific relationship we document between anticipated discrimination and masking. Still, consistent with the pattern documented in Table 6, we do find statistically significant gender differences in risk preferences for STEM/BE which can help explain part of the gender masking gap. In contrast, for non-STEM/BE, there is suggestive evidence that lower masking by female students may be driven by a lower knowledge of the policy and a higher relative tendency by male students to mask in order to focus on learning rather than grades. Preferences for transparency, meaning a decision not to mask because it would be deceiving or not accurately represent a student's ability, appear stronger for male students and therefore unlikely to have substantially contributed to the masking gap. In Table A5.3, we also show that the masking gap appears unaffected by whether respondents are more or less likely to pursue graduate studies.

4 Conclusion

We study a grading policy allowing students to mask their letter grades into a "Pass" excluded from their GPA, after having observed their original grade. We show robust evidence that female students are less likely to mask, accounting for differences in original grades, GPA, courses, and majors. We then present a framework showing how anticipated gender discrimination in the labor market could lead female students to mask less and test its predictions using a survey of students who were impacted by the policy. The survey confirms that students anticipate that female students will face discrimination in the labor market which decreases their incentives to mask.

Our results highlight how education choices, which are often studied through the lens of preferences, ability, or monetary returns, can also be distorted by anticipated discrimination before individuals even enter the labor market. More broadly, decisions to take certain courses, majors, extra-curricular activities, or to obtain a higher-education degree influence how a student signals their productivity and can create disparities if certain students expect different returns from these decisions. In our context, the masking policy was introduced by the university to soften the impact of the COVID-19 pandemic. Our results suggest that policies intended to help students may actually worsen gaps by background characteristics (in this case, gender). This should be taken into account when determining policy.

To our knowledge, our paper is one of few empirical studies to shed light on how education decisions are distorted by anticipated discrimination. Given that it is anticipated discrimination that matters for investment decisions (Coate and Loury, 1993), it is somewhat surprising how little empirical work there has been to date on this question. This is likely, in part, due to the fact that such an investigation typically entails the collection of ex-ante subjective perceptions of discrimination (in addition to behavior). Regardless, further work in this space should be immensely valuable.

Finally, while we find that students anticipate that females will be treated differently than males were they to mask their grades, we do not know if this in fact how employers would behave, or whether students under- or over- estimate the extent of discrimination. Students' perceptions – whether accurate or inaccurate – matter for their behavior. However, if these perceptions are systematically biased, there is room for policy interventions. This remains an open question.

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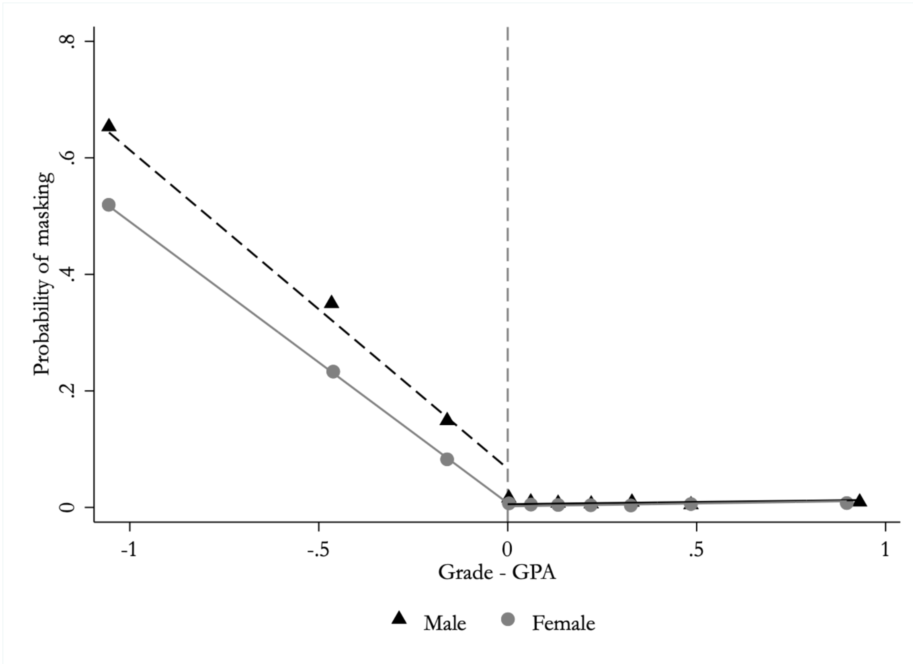
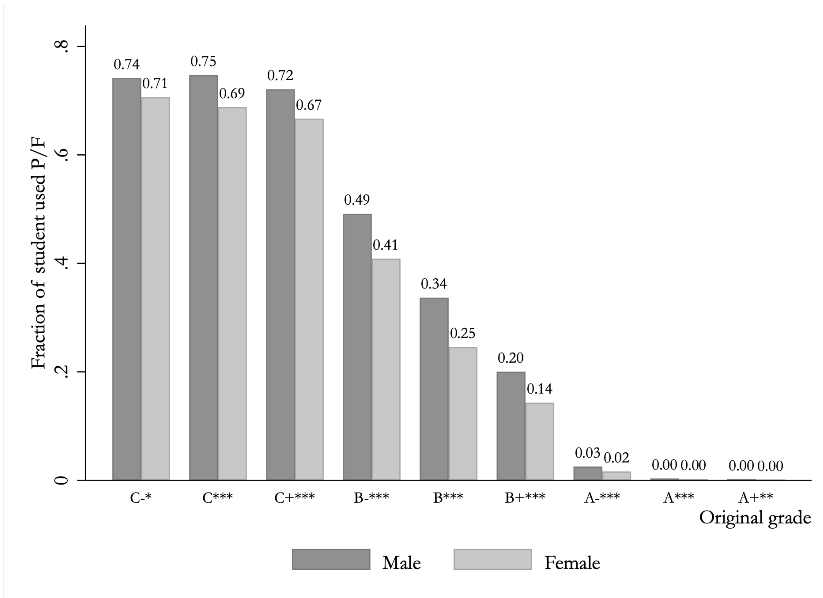
Figure 1: Probability of masking a grade and distance from a student's GPA



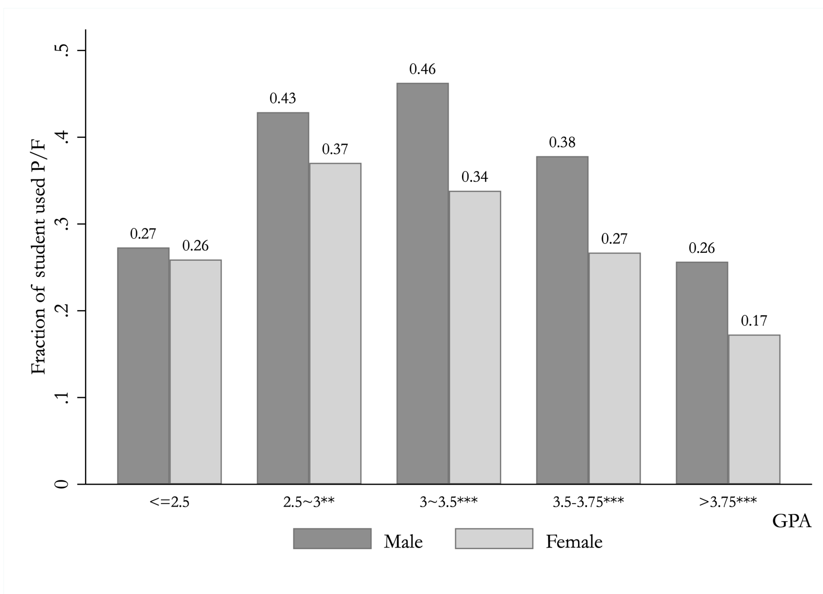
Notes: Grade-GPA is the difference between a student's original grade for a course and their incoming GPA.

Figure 2: Masking across grades and GPA

Panel (a)

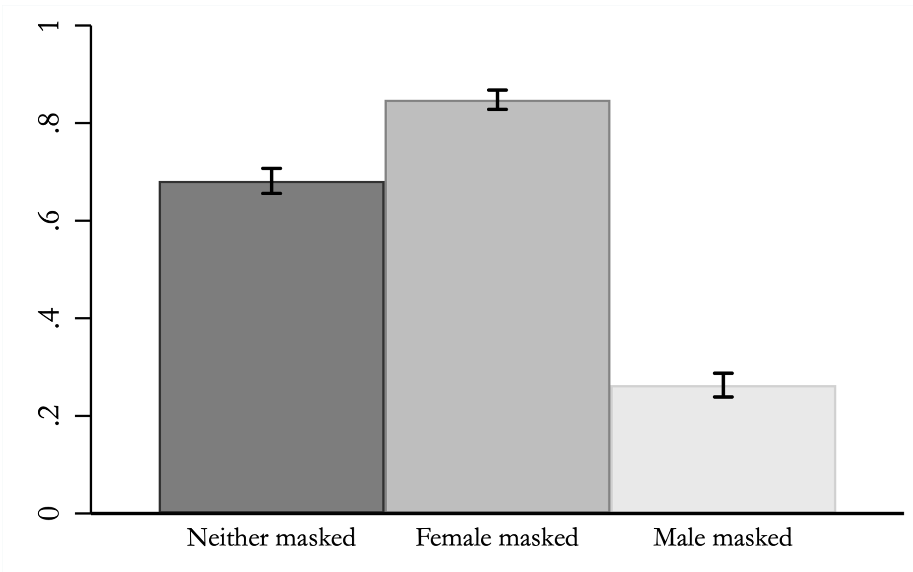


Panel (b)



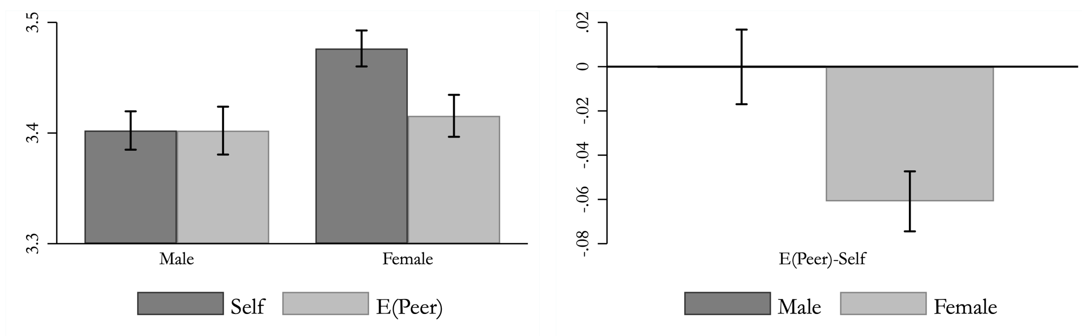
Notes: In Panel (a) original grade is the grade received before masking. In Panel (b) GPA is the incoming GPA at the time the grading policy was implemented.

Figure 3: Expected likelihood of a male applicant receiving a job offer, given equal qualifications



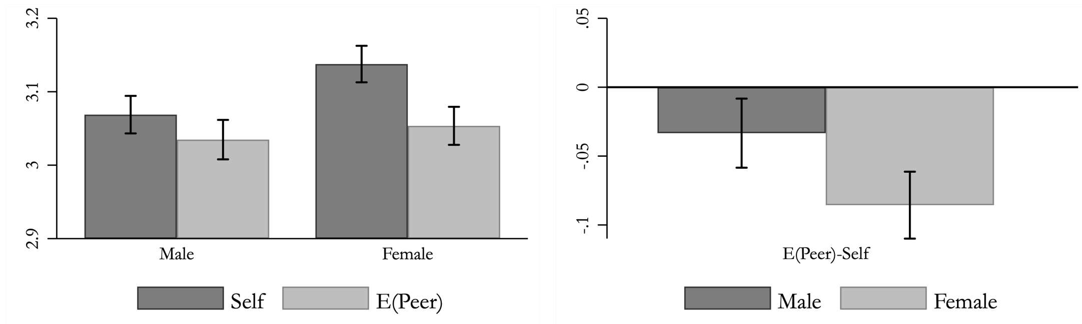
Notes: The corresponding survey question is: "Consider the case where an employer receives job applications from a UM male and female [STEM/BE or non-STEM/BE] major. Both have similar profiles and seem equally qualified. The employer can make only one offer. Who do you think the employer will make an offer to if [neither masked/both masked or the female applicant masked but not the male applicant/the male applicant masked but not the female applicant]." If both masked, 68% of students think the male applicant will receive the job offer. This figure pools male and female respondents and views about students in STEM/BE and non-STEM/BE together.

Figure 4: Expected GPA of students by gender, first and second-order beliefs



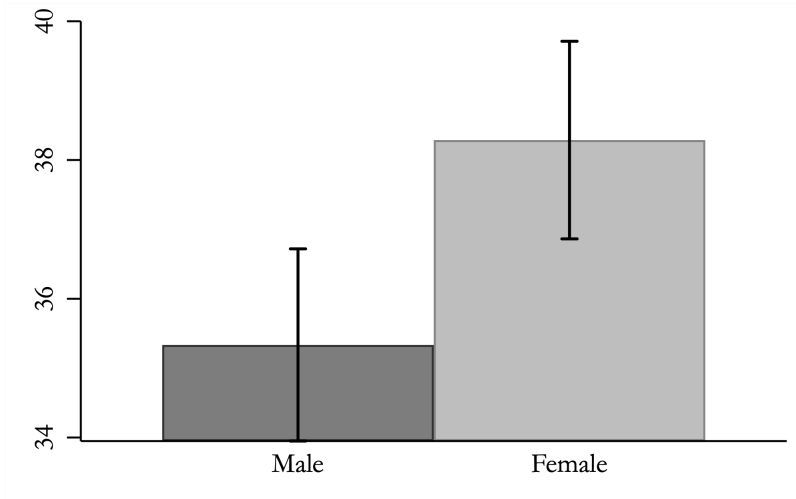
Notes: The corresponding survey question is: "What do you think the average GPA of male and female [STEM/BE or non-STEM/BE] students was?" and "How do you think your peers (other students) answered this question?" Self stands for the respondents' own beliefs (first-order) and E(peer) stands for their beliefs over peers (second-order). This figure pools male and female respondents and views about students in STEM/BE and non-STEM/BE together.

Figure 5: Expected inference about a masked grade by gender, first and second-order beliefs



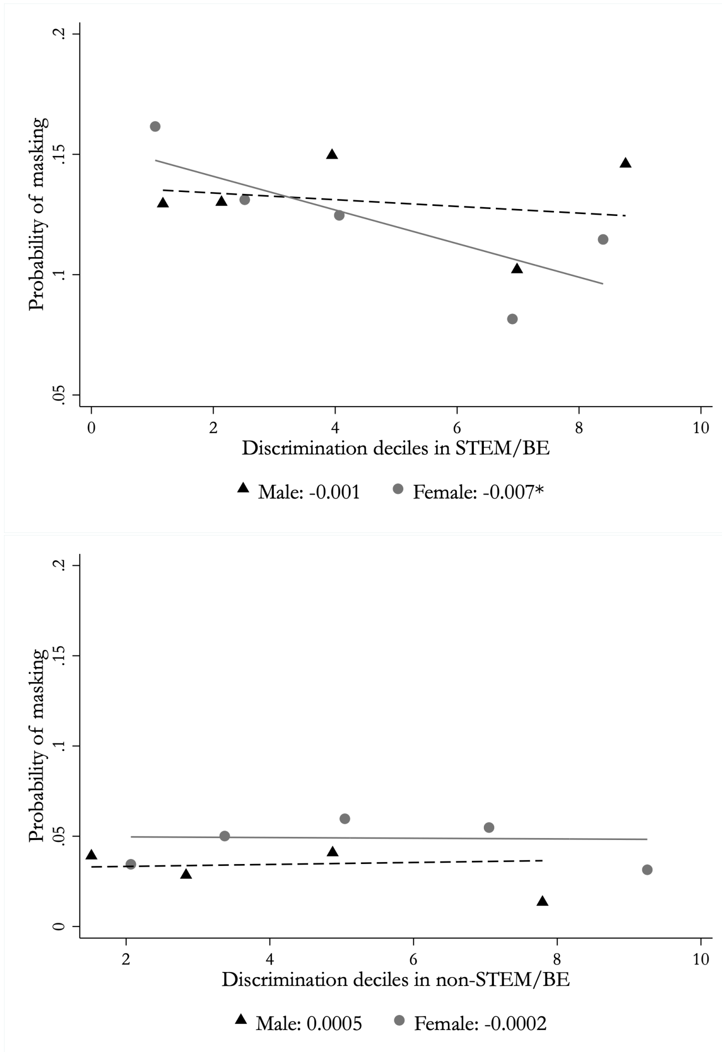
Notes: The corresponding survey question is: "Considering students in the following groups [STEM/BE female or STEM/BE male or non-STEM/BE female or non-STEM/BE male] who masked at least one grade, what do you think their original grade on that course would have been (on average)?" and "How do you think your peers (other students) answered this question?" Self stands for the respondents' own beliefs (first-order) and E(peer) stands for their beliefs over peers (second-order). This figure pools male and female respondents and views about students in STEM/BE and non-STEM/BE together.

Figure 6: Expected likelihood of an employer looking at individual grades by gender



Notes: The corresponding survey question is: "Consider 100 employers who receive resumes of students from this university. Of these 100 employers, how many do you think would take a look at some of the grades instead of only the overall GPA of the students if the resumes were those of [female or male] [STEM/BE or non-STEM/BE] majors." This figure pools male and female respondents and views about students in STEM/BE and non-STEM/BE together.

Figure 7: Likelihood of masking against the discrimination index



Notes: Controls include course grade, cumulative GPA, course difficulty, number of courses, number of letter-graded courses, mean and standard deviation of term grades, whether the course is a core course, and major fixed effects. The discrimination index is the sum of three -1/1 variables capturing whether a respondent anticipates discrimination against female students relating to their average GPA, their masked grades, and whether they believe that a male candidate would receive the employment offer when both genders mask a grade. Anticipated discrimination against female students in average GPA/masked grades = 1 if $FO_F - SO_F - (FO_M - SO_M) > 0$. FO_F and SO_F (FO_M and SO_M) stands for first-order and second-order beliefs of respondents about the average GPA/average masked grades of female (male) students. Anticipated discrimination against female students in employment = 1 if a male candidate would receive the offer when both genders mask a grade. The index is computed separately for views about students in STEM/BE and non-STEM/BE. Corresponding survey questions are described in Figures 3, 4 and 5. The index ranges from -3 to 3. The discrimination deciles for each major type are deciles of the discrimination index.

Table 1: Summary statistics

	Female	Male	P-value
Individual-term level			
Eligible students	29,343	27,760	
Used masking	0.227	0.332	0.000
Cumulative GPA	3.652	3.572	0.000
Term GPA	3.749	3.681	0.000
Credits taken	14.962	14.732	0.000
Credits earned	14.345	13.952	0.000
Conditional on masking			
Number of grades masked	1.457	1.647	0.000
Term GPA	3.718	3.678	0.000
Term GPA without masking	3.335	3.257	0.000
Term GPA gain	0.360	0.380	0.000
Grade level			
Number of grades	129,907	118,525	
Fraction masked	0.075	0.128	0.000
Pr(Masked grade $<$ GPA excluding masked grade)	0.965	0.968	0.129

Notes: There are 57,103 student-term records in Fall 2020 and Winter 2021, approximately 51.3 percent of which are from female students. Cumulative GPA is computed prior to the beginning of each term for Fall 2020 and Winter 2021.

Table 2: Use of the masking policy, at the individual level, intensive and extensive margins

	Used masking, odds ratio			Number masked | Used masking = 1		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.591***	0.640***	0.753***	-0.190***	-0.114***	-0.090***
	(0.013)	(0.017)	(0.020)	(0.015)	(0.014)	(0.015)
Cumulative GPA		2.539***	2.601***		0.237***	0.211***
		(0.132)	(0.140)		(0.026)	(0.026)
Term grade standard deviation		8.705***	10.103***		-0.896***	-0.826***
		(0.655)	(0.783)		(0.031)	(0.030)
Term grade average		0.279***	0.283***		-1.107***	-1.094***
		(0.017)	(0.018)		(0.031)	(0.031)
Course controls		YES	YES		YES	YES
Major FEs			YES			YES
Observations	57,103	49,061	49,061	15,857	14,196	14,196
Number of students	28,715	28,550	28,550	11,609	10,781	10,781
Mean of Y				1.567	1.592	1.592

Notes: Columns (1) to (3) report results of a logit regression of the log-odds for whether a student masked at least one of their grades in a given term onto row variables. Columns (4) to (6) report results of a linear regression for the number of grades masked by a student each term, conditional on masking at least one. Individual-clustered standard errors are reported in parentheses. ***, **, and * denote that estimates are statistically significantly different from one for columns (1) to (3) and from zero for columns (4) to (6) at the 1, 5, and 10% levels, respectively. Cumulative GPA is the incoming GPA for each term. Course controls for each term include average course difficulty, number of courses, number of letter-graded courses, and number of core courses. Course difficulty is measured by the average course grades of all students who took the course in the previous five years.

Table 3: Use of the masking policy, at the course level, odds ratio

	(1)	(2)	(3)	(4)
Female	0.550***	0.640***	0.557***	0.691***
	(0.012)	(0.019)	(0.018)	(0.022)
Course grade		0.045***	0.018***	0.016***
		(0.001)	(0.001)	(0.001)
Cumulative GPA			6.750***	6.673***
			(0.497)	(0.516)
Term grade standard deviation			0.630***	0.769***
			(0.046)	(0.055)
Term grade average			0.988	1.178***
			(0.054)	(0.064)
Course controls			YES	YES
Major FEs				YES
Observations	248,432	248,432	212,923	212,923
Number of students	28,715	28,715	28,550	28,550

Notes: The table reports results of a logit regression of the log-odds for whether a student masked a given course grade onto row variables. Individual-clustered standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from one at the 1, 5, and 10% levels, respectively. Course grade is the original grade obtained for the course, before masking. Cumulative GPA is the incoming GPA for each term. Course controls include course difficulty, number of courses for the term, number of letter-graded courses for the term, and whether the course is a core course. Course difficulty is measured by the average course grades of all students who took the course in the previous five years.

Table 4: Views on grade masking across gender from a survey of experts

Likelihood of masking across gender, all else equal	
Equally likely to mask	0.288
Male more likely to mask	0.178
Female more likely to mask	0.329
Observations	73

Notes: The corresponding survey question is: "Consider one male and one female student with identical cumulative GPAs and grades in a given course. Which student do you think would be more likely to mask their grade for the course?" Respondents consist of researchers in economics and education from North American and Western European academic departments.

Table 5: Discrimination index across fields and respondent gender

	Discrimination index
Views about STEM/BE females	
All respondents	0.890
STEM/BE respondents	0.805
STEM/BE female respondents	1.153
STEM/BE male respondents	0.402
Views about non-STEM/BE females	
All respondents	0.424
Non-STEM/BE respondents	0.570
Non-STEM/BE female respondents	0.667
Non-STEM/BE male respondents	0.205

Notes: The discrimination index is the sum of three -1/1 variables capturing whether a respondent anticipates discrimination against female students relating to their average GPA, their masked grades, and whether they believe that a male candidate would receive the employment offer when both genders mask a grade. The index ranges from -3 to 3. Anticipated discrimination against female students in average GPA/masked grades = 1 if $FO_F - SO_F - (FO_M - SO_M) > 0$. FO_F and SO_F (FO_M and SO_M) stands for first-order and second-order beliefs of respondents about the average GPA/average masked grades of female (male) students. Anticipated discrimination against female students in employment = 1 if a male candidate would receive the offer when both genders mask a grade. The index is computed separately for views about students in STEM/BE and non-STEM/BE. Corresponding survey questions are described in Figures 3, 4 and 5.

Table 6: Impact of anticipated discrimination on masking, odds ratio

	STEM/BE respondents				Non-STEM/BE respondents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.764	0.851	0.904	0.877	0.694	0.663	0.736	0.712
	(0.183)	(0.209)	(0.229)	(0.221)	(0.527)	(0.514)	(0.581)	(0.557)
Risk preferences		0.823**	0.827**	0.834**		1.088	1.026	0.973
		(0.070)	(0.071)	(0.072)		(0.317)	(0.304)	(0.300)
Discrimination index			0.889	1.106			0.685	0.385
			(0.103)	(0.165)			(0.249)	(0.400)
Female				0.580**				1.881
× Discrimination index				(0.137)				(1.993)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Major FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,617	1,617	1,617	1,617	757	757	757	757

Notes: The table reports results of a logit regression of the log-odds of masking onto row variables. Robust standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from one at the 1, 5, and 10% levels, respectively. Controls include course grade, cumulative GPA, course difficulty, number of courses, number of letter-graded courses, mean and standard deviation of term grades, and whether the course is a core course. The discrimination index for each major type is standardized into a variable with mean 0 and standard deviation 1. See Table 5 for additional details. Risk preference is constructed based on the survey question: "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" The value ranges from 1 to 7, with higher values indicating higher risk aversion.

Table 7: Survey evidence on other masking motives

	STEM/BE respondents			Non-STEM/BE respondents		
	Female	Male	P-value	Female	Male	P-value
Risk preferences	4.008	3.447	0.000	3.897	3.870	0.903
Care about grades	4.710	4.510	0.003	4.710	4.463	0.038
Masking motives						
Reason mask						
Letter grade was not needed	2.432	2.591	0.434	3.093	3.346	0.420
Focus on learning	2.591	2.774	0.368	2.628	3.115	0.183
Reason not mask						
Need letter grades for my major	3.873	3.374	0.008	3.609	3.214	0.221
Not know about the policy	1.827	1.879	0.760	1.766	1.536	0.349
Deceiving	2.807	2.967	0.396	2.375	2.679	0.337
Average across motives	2.707	2.504	0.033	2.405	2.136	0.112
Observations	238	206		107	54	

Notes: Care about grades and reasons for masking or not are based on survey questions asking, on a scale of 1 to 5, how strongly the respondent agreed with the related statements. For example, the statement for care about grades is "I care about my grades". Average across motives is an index across the five masking motives. The higher the value, the stronger the motive for not masking a grade. See Appendix 6 for corresponding survey questions.

Appendix 1 - Impact of grading policy on course taking and performance

Although our empirical analyses account for differences in grades and courses taken by students, it is useful to investigate whether the policy impacted overall student performance and course-taking. Similarly, since it was enacted during the COVID-19 pandemic, it is interesting to investigate whether performance and course-taking were systematically different during that period. To test these hypotheses, we use the following empirical specification and analyze the transcript data from 2020 to 2022:

$$Y_{it} = \beta_0 + \beta_1 Female_i + \beta_2 Year21/22_t + \beta_3 Year21_t +$$
$$\beta_4 Female_i \times Year21/22_t + \beta_{\mathbf{5}} Female_i \times Year21_t \times Year21/22_t$$
$$+ X_{it} + FE_{major} + u_{it},$$

where Y_{it} corresponds to an outcome of interest, namely number of credits attempted, number of credits earned, number of courses attempted, number of courses withdrew, number of courses failed, course difficulty, and cumulative GPA. $Year21/22_t$ is a binary variable taking the value one in the 2021 and 2022 academic years impacted by COVID. $Year21_t$ is a binary variable taking the value one in the 2021 academic year impacted by both the masking policy and COVID. In contrast, the vast majority of the 2020 academic year was impacted by neither COVID nor the masking policy, providing a comparison year.[9] $Female_i$ is an indicator for female students. β_5 is the parameter of interest capturing gender differences in course-taking or performance due to the masking policy. β_4 captures gender differences in course-taking or performance due to the COVID pandemic. Overall, Table A1 below shows that the masking policy had little impact on gender differentials in achievement and course taking: most estimates are statistically insignificant, and none of them are economically meaningful.

[9]The COVID pandemic started to create significant disruptions in the US for the first time around mid-March, too late to have affected course-taking and presumably too late to have affected credits/passing for the term.

Table A1: Course taking and student performance across academic years 2020, 2021, 2022

	(1) Credits attempted	(2) Credits earned	(3) Courses attempted	(4) Courses withdrew	(5) Courses failed	(6) Average course GPA	(7) Cumulative GPA
Female	0.457***	0.723***	0.187***	-0.022***	-0.004***	0.027***	0.154***
	(0.062)	(0.072)	(0.041)	(0.006)	(0.001)	(0.002)	(0.011)
Year 21/22	-0.489***	-0.755***	-0.117***	0.084***	0.015***	0.006***	0.113***
	(0.066)	(0.077)	(0.041)	(0.007)	(0.002)	(0.002)	(0.010)
Year 21	0.457***	0.247***	0.136***	0.022***	-0.021***	-0.002	0.115***
	(0.069)	(0.081)	(0.043)	(0.008)	(0.002)	(0.002)	(0.009)
Female × Year 21/22	0.273***	0.235**	0.043	0.005	-0.002	-0.003	-0.036***
	(0.088)	(0.103)	(0.058)	(0.010)	(0.002)	(0.002)	(0.013)
Female × Year 21/22	0.051	0.165	0.099*	-0.009	0.004*	0.004**	0.005
× Year 21	(0.092)	(0.108)	(0.059)	(0.011)	(0.002)	(0.002)	(0.011)
Program year	-1.556***	-1.507***	-1.640***	-0.005*	-0.001**	0.037***	-0.008***
	(0.021)	(0.025)	(0.014)	(0.003)	(0.000)	(0.001)	(0.003)
Constant	31.780***	30.520***	18.267***	0.214***	0.007**	3.449***	3.314***
	(0.237)	(0.266)	(0.141)	(0.025)	(0.003)	(0.005)	(0.034)
Major FE	YES	YES	YES	YES	YES	YES	YES
Observations	96,310	96,310	96,310	96,310	96,310	96,300	96,310
Number of students	49685	49685	49685	49685	49685	49683	49685
Mean of Y	28.126	26.795	13.760	0.229	0.009	3.546	3.493

Notes: The table reports results of regressions of course taking and performance outcomes onto row variables. The academic year 2020 was before the COVID pandemic, year 2021 was impacted by both the masking policy and by COVID, while year 2022 was only impacted by COVID. Individual-clustered standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from zero at the 1, 5, and 10% levels, respectively.

Appendix 2 - Comparison between survey respondents and student population

Table A2: Survey versus transcript samples

	Survey sample	Transcript sample	P-value
Female	0.58	0.51	0.00
Minority	0.13	0.13	0.86
Family income <$50k	0.19	0.13	0.00
Family income $50k-$100k	0.16	0.13	0.13
Family income $100k-$200k	0.23	0.22	0.71
Family income >$200k	0.21	0.28	0.00
SAT	1,423	1,399	0.00
STEM/BE major	0.68	0.63	0.05
Cumulative GPA	3.73	3.62	0.00
Used masking	0.28	0.27	0.67
Number of grades masked	0.40	0.43	0.40
Observations	542	28,748	

Notes: Minority indicates whether U.S. Citizens or U.S. Permanent Residents have self-identified as any of the following race/ethnicity (Hispanic; Native American; Black or African American; Native Hawaiian or Other Pacific Islander; Asian). Family income represents a student's estimated gross family income.

Appendix 3 - Comparison between survey responses and true average GPA and masked grades

Table A3.1: Deviation from true GPA and masked grades

	Female respondents	Male respondents	P-value	STEM/BE respondents	Non-STEM/BE respondents	P-value
Respondent belief - Avg. GPA						
Male STEM/BE	-0.144	-0.208	0.008	-0.171	-0.155	0.546
Female STEM/BE	-0.094	-0.175	0.000	-0.148	-0.073	0.003
Male non-STEM/BE	-0.012	-0.050	0.137	-0.029	-0.027	0.935
Female non-STEM/BE	-0.034	-0.097	0.007	-0.071	-0.040	0.224
Respondent belief - Avg. masked grades						
Male STEM/BE	0.266	0.380	0.002	0.336	0.237	0.018
Female STEM/BE	0.395	0.456	0.096	0.433	0.368	0.110
Male non-STEM/BE	0.270	0.443	0.000	0.350	0.301	0.244
Female non-STEM/BE	0.333	0.434	0.006	0.362	0.388	0.528

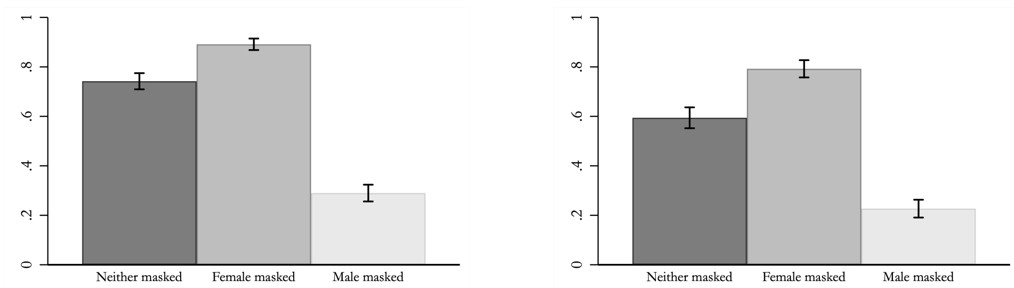
Notes: We compare survey responses to the true Winter 2020 cumulative GPA and average masked grades. See Figures 4 and 5 for additional details.

Appendix 4 - Additional survey evidence

Appendix 4.1 - Responses by gender of survey respondent

Figure A4.1.1: Expected likelihood of a male applicant receiving a job offer, given equal qualifications

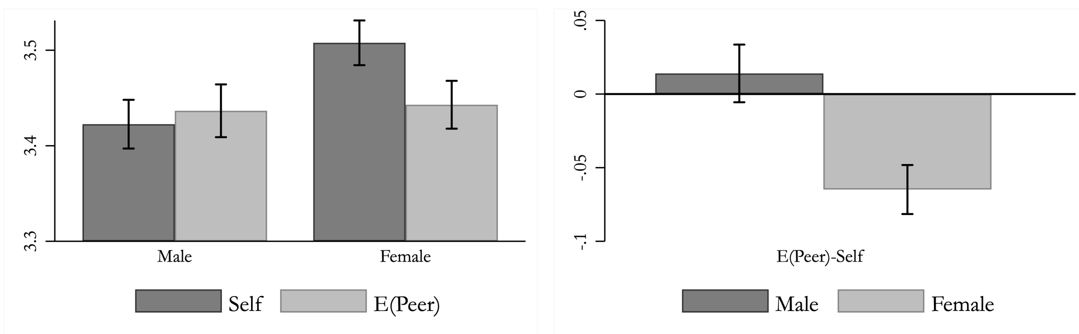
(a) Female respondents (b) Male respondents



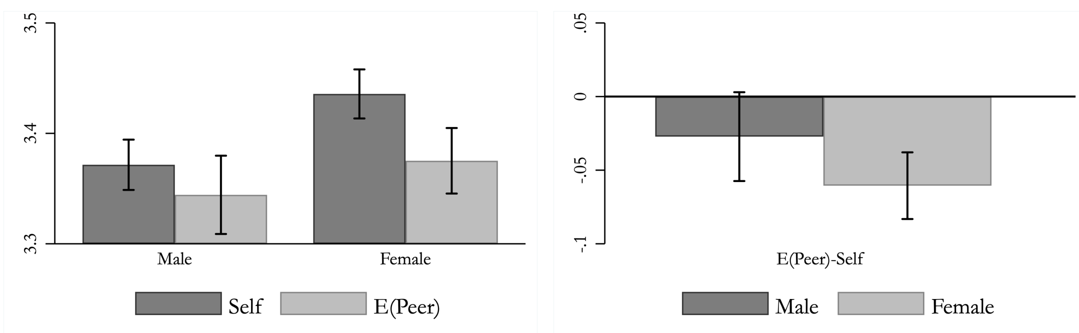
Note: This figure pools respondents' views about students in STEM/BE and non-STEM/BE together. See Figure 3 for additional details.

Figure A4.1.2: Expected GPA of students by gender, first and second-order beliefs

(a) Female respondents



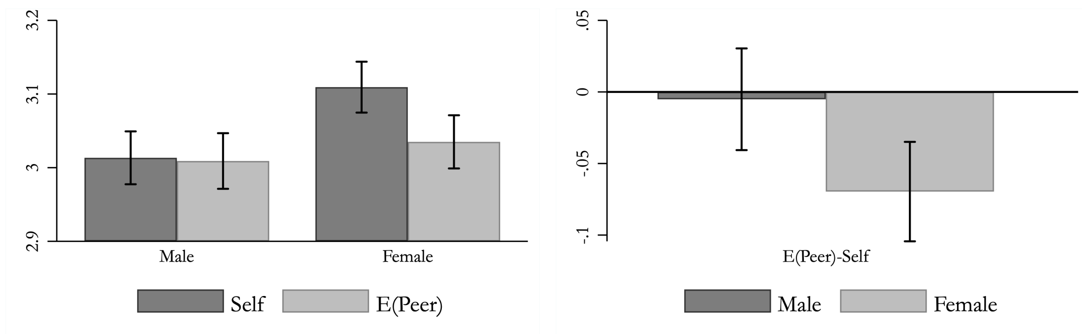
(b) Male respondents



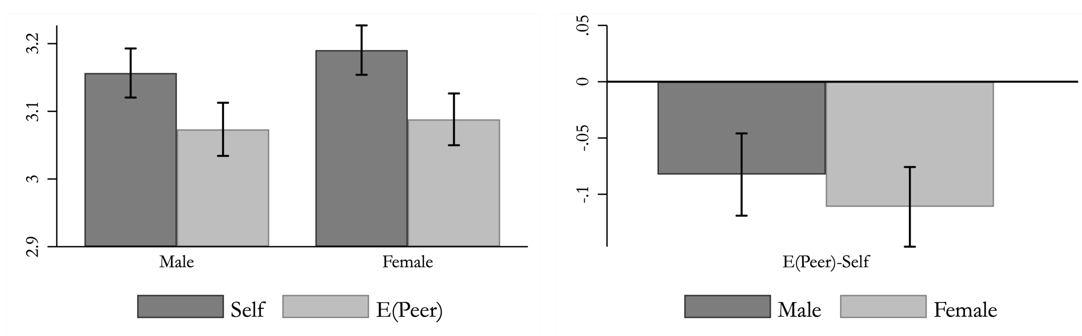
Notes: This figure pools respondents' views about students in STEM/BE and non-STEM/BE together. See Figure 4 for additional details.

Figure A4.1.3: Expected inference about a masked grade by gender, first and second-order beliefs

(a) Female respondents



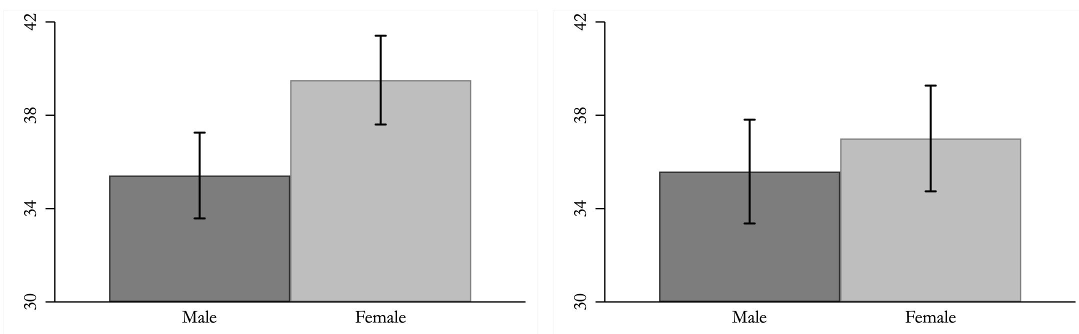
(b) Male respondents



Notes: This figure pools respondents' views about students in STEM/BE and non-STEM/BE together. See Figure 5 for additional details.

Figure A4.1.4: Expected likelihood of an employer looking at individual grades by gender

(a) Female respondents (b) Male respondents

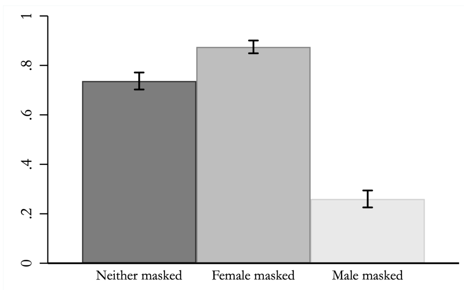


Notes: This figure pools respondents' views about students in STEM/BE and non-STEM/BE together. See Figure 6 for additional details.

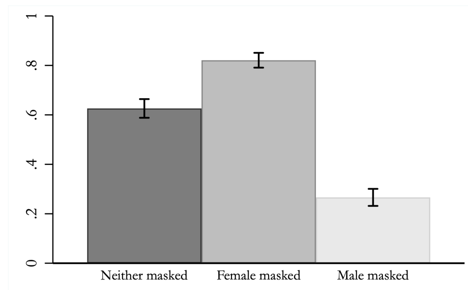
Appendix 4.2 - Responses by views about STEM/BE and non-STEM/BE

Figure A4.2.1: Expected likelihood of a male applicant receiving a job offer, given equal qualifications

(a) Views about students in STEM/BE



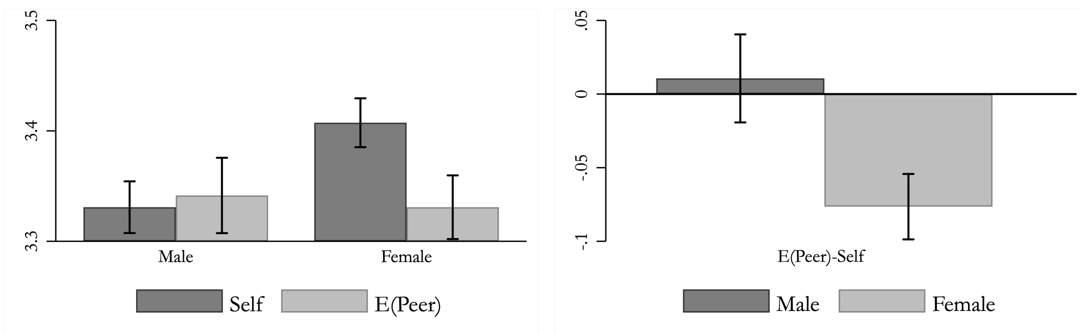
(b) Views about students in non-STEM/BE



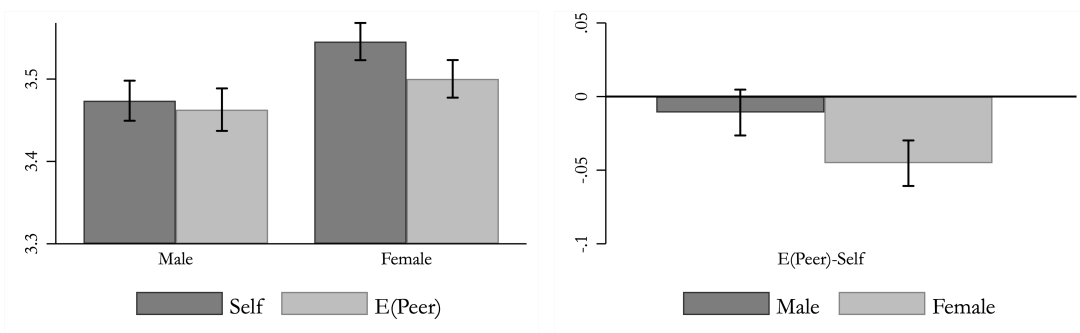
Note: This figure pools male and female respondents' views together. See Figure 3 for additional details.

Figure A4.2.2: Expected GPA of students by gender, first and second-order beliefs

(a) Views about students in STEM/BE



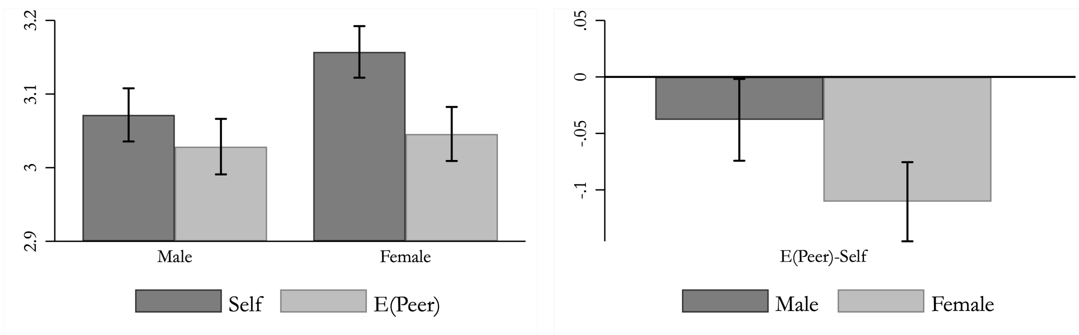
(b) Views about students in non-STEM/BE



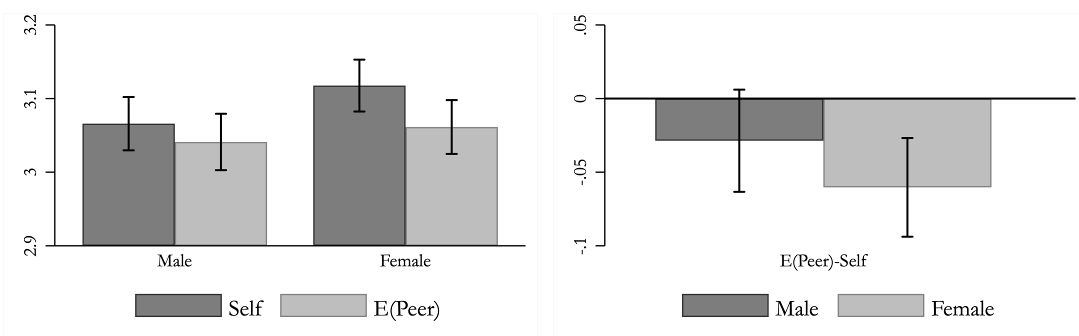
Notes: This figure pools male and female respondents' views together. See Figure 4 for additional details.

Figure A4.2.3: Expected inference about a masked grade by gender, first and second-order beliefs

(a) Views about students in STEM/BE



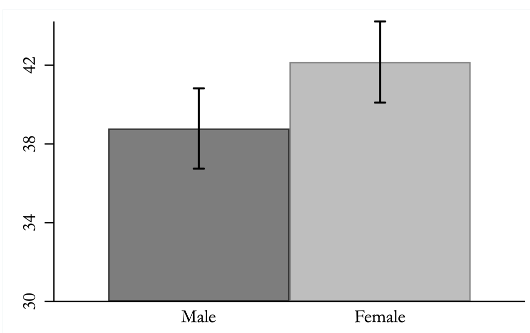
(b) Views about students in non-STEM/BE



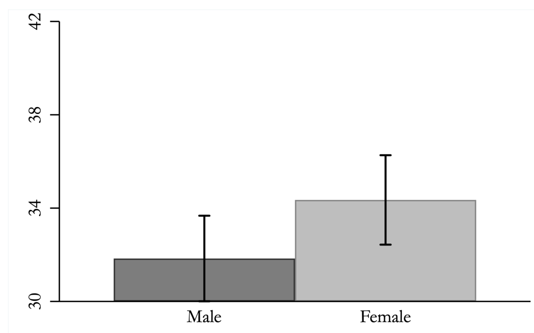
Notes: This figure pools male and female respondents' views together. See Figure 5 for additional details.

Figure A4.2.4: Expected likelihood of an employer looking at individual grades by gender

(a) Views about students in STEM/BE



(b) Views about students in non-STEM/BE



Notes: This figure pools male and female respondents' views together. See Figure 6 for additional details.

Appendix 5 - Robustness Checks

Table A5.1: Probability of masking at the course level, Linear Probability Model

	(1)	(2)	(3)	(4)
Female	-0.053***	-0.018***	-0.027***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Course grade		-0.339***	-0.375***	-0.401***
		(0.002)	(0.003)	(0.003)
Cumulative GPA			0.103***	0.109***
			(0.004)	(0.004)
Term grade standard deviation			0.026***	0.034***
			(0.005)	(0.005)
Term grade average			0.022***	0.047***
			(0.006)	(0.006)
Course controls			YES	YES
Course & Major FEs				YES
Observations	248,432	248,432	215,102	214,720
Number of students	28,715	28,715	28,550	28,550
Mean of Y	0.100	0.100	0.105	0.105

Notes: The table reports results of a linear regression of the probability of masking a grade onto row variables. Course grade is the original grade before masking. Cumulative GPA is the incoming prior GPA. Course controls include number of courses, number of letter-graded courses, and a dummy for core courses. Individual-clustered standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from zero at the 1, 5, and 10% levels, respectively.

Table A5.2: Heterogeneity in masking at the course level, Linear Probability Model

	First-year student (1)	Fourth-year student (2)	Core courses only (3)
Female	-0.007	-0.015***	-0.020***
	(0.006)	(0.003)	(0.004)
Cumulative GPA	0.047***	0.138***	0.124***
	(0.012)	(0.006)	(0.011)
Term grade standard deviation	0.050***	0.053***	-0.016
	(0.017)	(0.008)	(0.011)
Term grade average	0.069***	0.046***	0.010
	(0.019)	(0.009)	(0.012)
Course grade	-0.322***	-0.405***	-0.413***
	(0.010)	(0.004)	(0.006)
Course controls	YES	YES	YES
Course & Major FEs	YES	YES	YES
Observations	11,001	94,449	43,179
Number of students	2410	13044	17629
Mean of Y	0.089	0.099	0.143

Notes: The table reports results of a linear regression of the probability of masking a grade onto row variables. Course grade is the original grade before masking. Cumulative GPA is the incoming prior GPA. Course controls include number of courses, number of letter-graded courses, and a dummy for core courses. Individual-clustered standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from zero at the 1, 5, and 10% levels, respectively.

Table A5.3: Heterogeneity in masking based on graduate school plan, odds ratio

	Used masking (1)
Female	0.545 (0.232)
Graduate school	1.280 (0.434)
Female × Graduate school	0.961 (0.458)
Controls	YES
Major FEs	YES
Observations	548

Notes: The table reports results of a logit regression of the log-odds for whether a student masked at least one of their grades onto row variables. The corresponding survey question is: "How likely is it that you will pursue a post-bachelor's degree (such as a MD, PhD, Masters, etc.) at some point after graduation?" The regression controls for the student's GPA. Graduate school is a dummy variable capturing whether students are [very or somewhat] likely to go to graduate school. Robust standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from one at the 1, 5, and 10% levels, respectively.

Table A5.4: Robustness across definitions of course difficulty

	Average course grades (1)	Average SAT (2)
Female	0.691***	0.691***
	(0.022)	(0.022)
Cumulative GPA	6.692***	6.292***
	(0.511)	(0.474)
Term grade standard deviation	0.773***	0.770***
	(0.055)	(0.055)
Term grade average	1.166***	1.087***
	(0.063)	(0.059)
Course grade	0.016***	0.018***
	(0.001)	(0.001)
Course controls	YES	YES
Major FEs	YES	YES
Observations	213,607	214,995
Number of students	28,550	28,542

Notes: The table reports results of a logit regression of the log-odds for whether a student masked a given course grade onto row variables. Course grade is the original grade before masking. Cumulative GPA is the incoming prior GPA. Course controls include course difficulty, number of courses, number of letter-graded courses, and a dummy for core courses. Course difficulty corresponds to the average course grade (Column 1) or the average SAT score (Column 2) of all students who took the course in the last five years. Individual-clustered standard errors are reported in parentheses. ***, **, * denote that estimates are significantly different from one at the 1, 5, and 10% levels, respectively.

Appendix 6 - Survey

Start of Block: Section 1: Demographic Information

Time0 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q.Consent Please indicate your agreement to participate in this research study:

- ◯ Yes, I agree to participate in the research study. (1)
- ◯ No, I do not agree to participate in the research study. (2)

Skip To: End of Survey If Please indicate your agreement to participate in this research study: = No, I do not agree to participate in the research study.

Page Break

Time1 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q1.1 What is your current age?
(1)

▼ 16 (1) ... 50 (35)

Q1.2 What is your country of birth?

▼ Afghanistan (1) ... Other (1358)

Q1.3 Please state the gender with which you identify.

○ Male (1)

○ Female (2)

○ Non-binary / third gender (3)

○ Prefer not to say (4)

○ Prefer to self-describe (5)
____

Q1.4 What is your race/ethnicity? Please select all that apply

- ☐ White/Caucasian (1)
- ☐ Black/African American (2)
- ☐ American Indian (3)
- ☐ Hispanic/Latino (4)
- ☐ Asian/Pacific Islander (5)
- ☐ Prefer not to answer (6)
- ☐ Other (please specify) (7) ____

Q1.5 What fields are you majoring (or do you plan to major) in? List up to two fields.

Q1.5a Major 1 choice.
(1)

▼ Actuarial Mathematics (Sub-Major) (1) ... Other (134)

Q1.5b Major 2 choice. Select N/A if you are not planning to pursue a second major.
(1)

▼ N/A (1) ... Other (135)

Display This Question:

If Major 1 choice. = Other

Q1.5a_other You selected "other" for major 1 choice. Please write in your major below.

____

Display This Question:

If Major 2 choice. Select N/A if you are not planning to pursue a second major. = Other

Q1.5b_other You selected "other" for major 2 choice. Please write in your major below.

____

Q1.6 What fields are your minoring in (or planning to minor in)? Select N/A if you do not (plan to) have a minor.
(4)

▼ N/A (1) ... Yiddish Studies (117)

Q1.7 What is your cumulative grade point average (GPA)? (Please round up to the nearest tenth.)
(1)

▼ (1) ... 4 (32)

Q1.8 When do you expect to graduate?
(1)

▼ 2022 Fall (1) ... 2025 Summer (9)

Q1.9 Were you registered as a full-time student during Fall 2020 and Winter 2021?

◯ Yes, I was registered in both semesters (1)

◯ Yes, I was registered in Fall 2020 only (2)

◯ Yes, I was registered in Winter 2021 only (3)

◯ No, I was not registered in either semester (4)

Skip To: Not Eligible If Were you registered as a full-time student during Fall 2020 and Winter 2021? = No, I was not registered in either semester

Skip To: Not Eligible If Were you registered as a full-time student during Fall 2020 and Winter 2021? = Yes, I was registered in Fall 2020 only

Display This Question:

If Were you registered as a full-time student during Fall 2020 and Winter 2021? = Yes, I was registered in Fall 2020 only

Or Were you registered as a full-time student during Fall 2020 and Winter 2021? = No, I was not registered in either semester

Not Eligible Thank you for your interest in our survey but you are not eligible to take the survey. In order to participate you must be currently enrolled, and should have registered as a degree-seeking undergraduate student for the Winter 2021 semester.

Skip To: End of Survey If Thank you for your interest in our survey but you are not eligible to take the survey. In order t... Is Displayed

Q1.10 What were your scores on the SAT? Please write N/A if you did not take the SAT.

◯ Verbal (1) ____

◯ Math (2) ____

Q1.11 What was your composite score on the ACT? (Round up your score to the nearest integer; write N/A if this is not applicable to you)

○ (1) ____

Q1.12 What was your rank in your high school graduating class? Please answer on a 1-100 scale, where 1 means you ranked in the top 1%. If your school did not rank graduating classes then please estimate your ranking as best you can. Note that 100 means the lowest rank.

	1 11 21 31 41 51 60 70 80 90 100
()	

End of Block: Section 1: Demographic Information

Start of Block: Section 2:Perceptions

Time2 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Perceptions In some of the questions in this survey, we will ask you about students majoring in STEM/BE fields.
By **STEM/BE** fields, we mean majors in “Science, Technology, Engineering, and Math” OR in Business/Economics.
By **non-STEM/BE** fields, we mean all other majors (many of which are in the humanities, arts, public health, other social sciences, etc.).

In 2019, even though female students made up 51% of the undergraduate student body here, they comprised only 45% of all STEM/BE majors but 64% of all non-STEM/BE majors. **That is, female students were more likely to major in non-STEM/BE fields, and male students in**

STEM/BE fields. These statistics are from 2019, the academic year before Covid. However, the statistics have largely been the same before 2019, as well as after.

Please answer the next questions carefully. In many questions, there is no correct or wrong answer - we are simply interested in your beliefs. However, in some questions, you can earn extra money if your answer is correct.

Q2.0 Is your primary major in a STEM/BE field?

○ Yes (1)

○ No (2)

Page Break

Q2.1 Consider all students who graduated from here with a STEM/BE major in 2019. What do you think the average GPA of male and female **STEM/BE** students was? Please answer on a 0-4 scale.

Again, by STEM/BE we mean majors in Science, Technology, Engineering, Math, OR Business/Economics.

○ Average GPA of **male STEM/BE** students (1) ____

○ Average GPA of **female STEM/BE** students (2) ____

Q2.2 The prior question was also asked to other current students. We would like to know how you think **your peers (other students)** answered this question. We will randomly choose one of your two guesses and you will receive $0.25 if it is within 0.025 GPA points of the actual average guess of the other survey respondents. Please answer on a 0-4 scale.

○ My guess of what the other students said was the average GPA of **male STEM/BE** students (1) ____

○ My guess of what the other students said was the average GPA of **female STEM/BE** students (2) ____

Page Break

Perceptions_NonSTEM We will now ask you the same two questions, but regarding **non-STEM/BE** majors. By non-STEM/BE majors, we mean majors in fields such as the humanities, arts, public health, other social sciences, etc.

Q2.3 Consider all students who graduated from here with a **non-STEM/BE** major in 2019. What do you think the average GPA of male and female non-STEM/BE students was? Please answer on a 0-4 scale.

- ○ Average GPA of **male non-STEM/BE** students (1) ____
- ○ Average GPA of **female non-STEM/BE** students (2) ____

Q2.4 The prior question was also asked to other current students. We would like to know how you think **your peers (other students)** answered this question. We will randomly choose one of your two guesses and you will receive $0.25 if it is within 0.025 GPA points of the actual average guess of the other survey respondents. Please answer on a 0-4 scale.

- ○ My guess of what the other students said was the average GPA of **male non-STEM/BE** students (1) ____
- ○ My guess of what the other students said was the average GPA of **female non-STEM/BE** students (2) ____

End of Block: Section 2:Perceptions

Start of Block: Section3: Masking

Q3.1 During the 2020-2021 academic calendar, the university had a flexible undergraduate policy. Specifically, in the Winter 2021 semester, students could change their letter grades between A+ and C- to a Pass, after seeing their final letter grade. Were you aware of this “masking” policy?

- ◯ Yes (1)
- ◯ No (2)

Q3.2 Based on our analysis, we found that 27.6% of undergraduate students masked at least one grade during the Winter 2021 semester. Again, by masking, we mean changing a letter grade to a Pass.

What is your best guess of the percent of the following groups that **masked at least one grade** during the Winter 2021 semester here. Please answer on a 0-100 scale for each question, where 100 means all the students in that group masked at least one grade.

	0 10 20 30 40 50 60 70 80 90 100
% of Male STEM/BE majors ()	
% of Female STEM/BE majors ()	
% of Male non-STEM/BE majors ()	
% of Female non-STEM/BE majors ()	

Q3.3 Considering students in the following groups who masked at least one grade, what do you think their **original grade** on that course would have been (on average)?

Q3.3.1 **Male STEM/BE** majors who masked at least one grade (12)

▼ A/A+ (1) ... C- (8)

Q3.3.2 **Female STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Q3.3.3 **Male non-STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Q3.3.4 **Female non-STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Q3.4.1 We asked the same question to other students. How do you think they answered this question?

My guess of what my **peers** thought was the **original course grade**:

Q3.4.1 **Male STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Q3.4.2 **Female STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Q3.4.3 **Male non-STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Q3.4.4 **Female non-STEM/BE** majors who masked at least one grade
(12)

▼ A/A+ (1) ... C- (8)

Page Break

Q3.5 Assume a scenario where you send your resume to 100 employers. **Given your major and your GPA,** of these 100 employers, when looking at your application, how many do you think would take a look at some of your **grades** instead of only your overall GPA (0-100)?

	Number of employers 0 10 20 30 40 50 60 70 80 90 100
()	

Q3.6 Consider 100 employers who receive resumes of students. Of these 100 employers, how many do you think would take a look at some of the **grades** instead of only the overall GPA of the students if

	0 10 20 30 40 50 60 70 80 90 100
The resumes were those of **male STEM/BE** majors ()	
The resumes were those of **female STEM/BE** majors ()	
The resumes were those of **male non-STEM/BE** majors ()	
The resumes were those of **female non-STEM/BE** majors ()	

Page Break

Q3.7 Consider the case where an employer receives job applications from a male and female **STEM/BE** major. Both have similar profiles and seem equally qualified. The employer can make only **one** offer. Who do you think the employer will make an offer to if:

	Male applicant (1)	Female applicant (2)
Both the male and female applicant do not mask any grades (1)	○	○
Both the male and female applicant mask a grade (2)	○	○
The male applicant masks a grade but the female applicant does not (3)	○	○
The male applicant does not mask a grade but the female applicant does (4)	○	○

Q3.8 The same question was asked to other students. What is your guess of the percent of students who said the employer would hire the **male STEM/BE** major applicant (instead of the female STEM/BE major applicant) in each scenario (0-100)?
Please answer carefully. We will pick one of these questions at random. If your guess is correct (that is, within 1 percentage point of the actual percent), you will receive $0.25.

What % of your **peers** said the employer would hire the **male** applicant:

	0 10 20 30 40 50 60 70 80 90 100
If both the male and female applicant do not mask any grades ()	
If both the male and female applicant mask a grade ()	
If the male applicant masks a grade but the female applicant does not ()	
If the male applicant does not mask a grade but the female applicant does ()	

Page Break

Q3.9 Now consider the case where an employer receives job applications from a male and female **non-STEM/BE** major. Both have similar profiles and seem equally qualified. The employer can make only **one** offer. Who do you think the employer will make an offer to if:

	Male applicant (1)	Female applicant (2)
Both the male and female applicant do not mask any grades (1)	○	○
Both the male and female applicant mask a grade (2)	○	○
The male applicant masks a grade but the female applicant does not (3)	○	○
The male applicant does not mask a grade but the female applicant does (4)	○	○

Q3.10 The same question was asked to other students. What is your guess of the percent of students who said the employer would hire the **male non-STEM/BE** major applicant (instead of the female non-STEM/BE major applicant) in each scenario (0-100)?
Please answer carefully. We will pick one of these questions at random. If your guess is correct (that is, within 1 percentage point of the actual percent), you will receive $0.25.

What % of your **peers** said the employer would hire the **male** applicant:

	0 10 20 30 40 50 60 70 80 90 100
If both the male and female applicant do not mask any grades ()	
If both the male and female applicant mask a grade ()	
If the male applicant masks a grade but the female applicant does not ()	
If the male applicant does not mask a grade but the female applicant does ()	

End of Block: Section3: Masking

Start of Block: Section4: Demographics (Continued)

Q4.1 Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you change a letter grade to Pass?

◯ Yes (1)

◯ No (2)

Display This Question:

If Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you chan... = Yes

Q4.1.1 How many course grades did you mask?
(1)

▼ 1 (1) ... More (6)

Display This Question:

If How many course grades did you mask? = 1

Q4.1.2 What was the original grade of the course you masked?
(1)

▼ A/A+ (1) ... C- (8)

Display This Question:

If How many course grades did you mask? != 1

And Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you chan... = Yes

Q4.1.3 You said you masked multiple course grades. What was the worst grade among the courses you masked?
(1)

▼ A/A+ (1) ... C- (8)

Display This Question:

If Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you chan... = Yes

Q4.1b How important were each of the following reasons in deciding to mask a grade

	Not at all important (1)	Slightly important (2)	Moderately important (3)	Very important (4)	Extremely important (5)
My GPA would have been negatively impacted had I not done so (1)	○	○	○	○	○
Taking the course with a letter grade was not needed (2)	○	○	○	○	○
I could focus on learning rather than worrying about the grade (3)	○	○	○	○	○

Display This Question:

If Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you chan... = Yes

Q4.1b_other If you have other reasons in deciding to mask a grade, please specify.

	Not at all important (1)	Slightly important (2)	Moderately important (3)	Very important (4)	Extremely important (5)
Other (please specify) (1)	○	○	○	○	○

Display This Question:

If Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you chan... = No

Q4.1c How important were each of the following reasons in deciding NOT to mask a grade?

	Not at all important (1)	Slightly important (2)	Moderately important (3)	Very important (4)	Extremely important (5)
I had good grades and didn't need to mask a grade (1)	○	○	○	○	○
I have to take courses for letter grades for my major (2)	○	○	○	○	○
I did not know about the policy, or about how to do it (3)	○	○	○	○	○
I thought that my employment opportunities would be negatively impacted by masking a grade (4)	○	○	○	○	○
I thought that graduate school admission chances would be negatively impacted by masking a grade (5)	○	○	○	○	○
I thought that masking a grade could be deceiving or not truly represent my performance in the course (6)	○	○	○	○	○

Display This Question:

If Did you make use of the “grade masking” policy in the Winter 2021 semester? That is, did you chan... = No

Q4.1c_other If you have other reasons in NOT deciding to mask a grade, please specify.

	Not at all important (1)	Slightly important (2)	Moderately important (3)	Very important (4)	Extremely important (5)
Other (please specify) (1)	○	○	○	○	○

Q4.2 On a scale of 1-5, how strongly do you agree with the following statements?

	1 - Strongly Disagree (1)	2 - Slightly Disagree (2)	3 - Neutral (3)	2 - Slightly Agree (4)	5 - Strongly Agree (5)
I care about my grades (1)	○	○	○	○	○
Letter grades are important because they signal a person's actual ability (2)	○	○	○	○	○
Letter grades are important because employers value them (3)	○	○	○	○	○
Letter grades are important for applying to graduate school (4)	○	○	○	○	○
Letter grades are important for motivation (5)	○	○	○	○	○
Letter grades are important because of my family's or friends' expectations (6)	○	○	○	○	○
Letter grades are important because I believe it is important to be transparent (7)	○	○	○	○	○

Q4.3 What do you think is the minimum GPA employers would have required to hire you if you majored in a

- ◯ STEM/BE field (1) ____________________
- ◯ Non-STEM/BE field (2) ____________________

Q4.4 Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please select a number between 1 and 7 where 1 means “absolutely unwilling to take risks” and 7 means “fully prepared to take risks”.

	1	2	3	4	5	6	7
Risk Preference ()							

Q4.5 How likely is it that you will pursue a post-bachelor's degree (such as a MD, PhD, Masters, etc.) at some point after graduating from here?

- ◯ Very likely (1)
- ◯ Somewhat likely (2)
- ◯ Somewhat unlikely (3)
- ◯ Very unlikely (4)

Q4.6 What is the most likely career you plan to pursue after college?

- ◯ Medical or healthcare professional (nurse, medical doctor, dentist, pharmacist, etc.) (1)
- ◯ Lawyer (2)
- ◯ Engineer (computer science or software, electrical, mechanical, etc.) (3)
- ◯ Pre-K-12 Teacher (4)
- ◯ Researcher (in natural sciences or social sciences) (5)
- ◯ Business/Finance (analyst, consultant, etc.) (6)
- ◯ Federal or state government professional (7)
- ◯ Career in the arts or entertainment (publishing and writing, graphic design, etc.) (8)
- ◯ Other (please list) (9) ____

End of Block: Section4: Demographics (Continued)

Start of Block: Submission

Submit Thank you for completing our survey. Press the right arrow below to submit your survey.

If you are selected for one of the $10 Amazon gift cards or qualify for compensation based on the accuracy of your answers, the study team will contact you within 6 weeks after the end of the survey with information on how to claim your prize.

End of Block: Submission
