Test-optional Admissions and Job Market Performance: Experimental Evidence from Japan*

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Abstract

We analyze how test-optional admissions affect students' job market outcomes. To this end, we conduct an experiment that corrects employers' misperceptions about the prevalence of test-optional admissions in Japan, where both test-optional and test-based admissions coexist within the same schools and programs. We find that test-optional admissions function as a signal of students' ability and induce statistical discrimination against test-optional applicants during resume screening. This discount applied to test-optional applicants is particularly pronounced at lower-ranked institutions, which tend to enroll students from lower socioeconomic backgrounds. Consequently, the adoption of test-optional admissions may disproportionately harm these students in the labor market.

Keywords: Test-optional admissions; Survey experiment; Job market; Statistical discrimination; Inequality

JEL classification: C91, J22, J24, J71

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1 Introduction

More and more colleges in the US adopt the “test-optional” admission policy: Students are no longer required to submit test scores to apply for a college. Outside the US, many countries that used to rely heavily on test scores, such as Australia, China, England, France, Japan, and South Korea, now adopt elements of the holistic admissions similar to the United States so that they rely less on test scores in college admission (Bastedo 2021). There is a growing body of literature that analyzes how such test-optional admission policies affect students’ college experience, such as diversity of the student body, especially in terms of admitting students from disadvantaged backgrounds, and dropout rates (e.g., Saboe and Terrizzi 2019; Dynarski, Nurshatayeva, Page and Scott-Clayton 2023; Sacerdote, Staiger and Tine 2025; Borghesan 2023; Onozuka 2025; Dessein, Frankel and Kartik 2025). However, little is known about how test-optional admission policies affect students *after* college life once they enter the job market. The introduction of test-optional admissions could affect job market performance if employers believe that test-optional admissions changes the composition of a university’s student body, which is exactly what test-optional admissions intend to achieve. Does the adoption of test-optional admissions benefit or harm students later in the job market? If so, what type of colleges or students are most affected?

This paper analyzes how the adoption of test-optional admissions affects the job market performance of university graduates. Answering this requires overcoming an important identification challenge: test-optional admission is correlated with many other factors, such as school name and curriculum. To isolate the effect of test-optional admissions, we conduct a novel online survey experiment in Japan, in which we ask workers at human resources departments to evaluate fictitious job resumes of new graduates in a way that closely mimics the real-world screening of job resumes. In designing the experiment, we exploit a unique institutional feature of Japanese college admission: both test-based and test-optional admissions co-exist for the same program of the same college, but different colleges and programs allocate very different fraction of seats to test-optional admissions. As a result, for a given school and program, an individual employer has only an imperfect knowledge about the fraction of students admitted through test-optional admissions (hereforth, we call them “test-optional students” for brevity).

In our survey, after eliciting the perceived fraction of test-optional students for a given school and program pair, we experimentally correct such respondents’ misperception by informing the true fraction of test-optional students only to the treatment group. If employers discount test-optional students, we expect that correcting their overestimation of the fraction of test-optional students leads to higher evaluation of the job resumes, and vice versa. In contrast, if employers are indifferent between test-optional and test-based students, then our information intervention should have no effect. As such, our experiment allows us to analyze whether test-optional students are evaluated differently in the job market.

We find that test-optional students are penalized in the job market. This is consistent with the interpretation that test-optional students suffer from statistical discrimination, which leads to worse outcomes in the job market. We also find that the discrimination of test-optional students is particularly significant among students of less-selective colleges. A potential explanation is that employers penalize test-optional students because their ability is on average lower or it has higher variance, which our survey results are consistent with.[1] Firms may expect that test-optional students from less-selective colleges have a high risk of not satisfying a minimum ability threshold, leading to severe statistical discrimination.

We also conduct several additional analyses to supplement our main finding. First, we construct a "pro-exam index" using a series of attitudinal questions about whether an employer thinks test-optional students have, on average, superior or inferior ability compared to test-based students. Using this index, we find that our experimental intervention has a larger impact among employers who have more negative views about test-optional students, consistent with the interpretation that our experimental results are indeed driven by employers' aversion toward hiring test-optional students. Second, we explore heterogeneity in the discount against test-optional students in terms of job applicants' gender, respondents' gender, respondents' firm size, and whether the respondents themselves used test-optional admissions. We find little heterogeneity in these dimensions. Third, we find little evidence that experimenter demand effects spuriously drive our results.

Overall, in the job market, the adoption of test-optional admissions could be harmful for students because employers value passing test-based admissions as a signal of students' true ability. This effect could be particularly harmful for students from less-selective colleges. This may represent an unintended consequence of a policy designed to support students from disadvantaged backgrounds: Given that students from disadvantaged socioeconomic backgrounds are more likely to attend less-selective colleges in Japan (Fujihara and Ishida 2016) and elsewhere (Buchmann, Condron and Roscigno 2010; Gerber and Cheung 2008), test-optional policies—though often designed to promote diversity and equity—may unintentionally disadvantage such students in the job market.

This paper contributes to a growing body of literature that analyzes the consequences of test-optional admission. Prior studies mostly focus on outcomes at college, such as whether it leads to more diversity in colleges or it leads to higher dropout rates (e.g., Saboe and Terrizzi 2019; Dynarski et al. 2023; Borghesan 2023; Sacerdote et al. 2025; Onozuka 2025; Dessein et al. 2025).[2] However, little is known about the causal effect of adopting a test-optional admission policy on students' outcomes after college life.[3] While a few studies descriptively compare labor earnings after graduation of students admitted through test-optional and test-based admissions (e.g., Urasaka, Nishimura, Hirata and Yagi 2013; Onozuka 2025), they do not address the endogeneity that arises from student self-selection: Students can tailor their college applications to test-optional and test-based admission policies. In contrast, motivated by correspondence studies in

[1] For theories of statistical discrimination based on the variance of the underlying ability, see Aigner and Cain (1977); Heckman and Siegelman (1993); Dickinson and Oaxaca (2009); Neumark (2018).

[2] Arcidiacono, Kinsler and Ransom (2022), Bleemer (2023), and Boehm and Carril (2024) also discuss the effect of admission policies that do not solely depend on the test scores.

[3] Although not in the context of test-optional admissions, Machado, Reyes and Riehl (2025) recently presents evidence that introduction of affirmative actions harms the job market performance of (non-affirmative action) graduates.

job applications (e.g., Bertrand and Mullainathan 2004) and information intervention (e.g., Haaland, Roth and Wohlfart 2023) in the experimental literature, we design a new survey experiment that utilizes Japan's unique institutional setting to identify the causal effect of test-optional admission on job market performance. We provide novel evidence that test-optional admissions may induce statistical discrimination by providing a signal of students' ability in the job market, and such statistical discrimination may be particularly salient among students from lower-ranked colleges.

The rest of this paper is organized as follows. Section 2 describes key background information on Japanese college admission systems. Section 3 presents our hypothesis and experimental design. Section 4 reports our main results, along with supplementary analyses. Section 5 concludes the paper.

2 Background: College admission systems in Japan

The current Japanese college admission system is characterized by the coexistence of test-based and test-optional admissions. Historically, Japan relied on standardized exams as the cornerstone of meritocratic selection since its modernization era (Amano 1990). Performance on entrance examinations serves as a strong proxy for students' ability, and it is widely believed that the prestige of the institution a student attends—rather than the specific field of study—functions as a key signal in the job market (Li, Urakawa and Suga 2023; Ono 2007). The importance of college entrance exam as a proxy of students' ability reflects two institutional features of Japan. First, college dropout rates are relatively low compared to many other countries (OECD 2009), implying that selection at the admission stage is highly informative of students' underlying ability.[4] Second, Japanese firms adopt a distinctive human capital development system, which prioritizes firm-specific skills gained through on-the-job training over general skills acquired through college education (Estevez-Abe, Iversen and Soskice 2001; Ito and Hoshi 2020). This means that employers may highly value applicants' general ability over the specific training they received in a university, making the ability as of college entrance highly informative of performance at the job.

While the traditional test-based admissions are called "general admissions" (*Ippan nyūshi*), Japanese higher education institutions have gradually introduced non-test-based admissions in response to the concern that the traditional written examination system induces excessive pressure on students, harming their mental health, stifling their creativity, and leaving no time for other activities (Entrich 2018). These newly established a new type of admission typically aim to evaluate applicants based on their aptitudes, motivations, and interests through school grades, essays, interviews, and extracurricular records (Ministry of Education 2000). The clearest form of such

[4] The dropout rates of private universities in Japan was around 8% (Yomiuri Shimbun Kyoiku Network 2019), which is substantially lower than the OECD average of 31% (OECD 2009). We also do not find evidence that dropout patterns substantially differ by admission type. For instance, Yamashita (2014) finds that students' intentions to drop out do not vary by admission type. In this study, we therefore expect that differences in dropout rates are unlikely to explain any penalties faced by graduates admitted through test-optional pathways.

non-test-based admissions is the "school recommendation admissions" (*Gakkō suisen nyūshi*).[5] Applying for school recommendation admissions requires students to obtain endorsement from their high school principal, based primarily on their academic performance and extracurricular activities in high school. Although students have the option to take external examinations in English, mathematics, and other subjects to demonstrate their aptitude and thereby qualify for endorsement, these examinations can be substituted with strong high school grades. The admission rate is typically near 100% once they could successfully apply, although the universities typically require some interviews and essays. In this sense, unlike the traditional test-based admissions, the applicants are not asked to take any high-stake exams (Nakamura 2011). Overall, these admissions do not require test scores, which marks a stark contrast from the traditional test-based admissions. Hereforth, we refer to the school recommendation admissions as "test-optional admissions."

Importantly, both test-based and test-optional pathways are available even for the same department at the same university, although the share of test-optional students differ substantially across different schools and departments.[6] Figure 1 illustrates this pattern among the Japanese universities included in our experiment. Even within the same university and program in the same year, some students are admitted through test-based examinations, while others enter via holistic, test-optional pathways. Figure 1 illustrates the situation for schools and programs in our sample: Some school-program combinations admit more than half of their students through test-based admissions, while others admit only around 20–30%. This substantial heterogeneity across schools and programs suggests that people may not accurately know the true share of students admitted through test-optional pathways, which we indeed confirm in our survey. This unique institutional feature of Japanese college admissions enables us to design an experiment that isolates the labor market effects of test-optional admissions while conditioning on cohort, department, and institution.

Anecdotal evidence suggests that even within the same university and the department, students admitted through holistic admissions are often perceived as less academically capable than their peers admitted through high-stakes testing (Hayashi 2012; Ishii 2014) and such concerns have also been repeatedly expressed in popular media.[7] Consistent with this view, Dahis, Schiavon and Scot (2025) recently provides evidence that competitive admission exams can select candidates with good performance on the job. However, it is not clear whether students admitted through test-

[5] In addition to school recommendation admissions, there are other forms of non–general admissions that do not require endorsement by a high school principal, such as the "holistic admissions (Sōgō-gata Senbatsu, formerly known as AO admissions)" or "self-recommendation admissions" (Jiko suisen nyūshi). Although these alternatives put less emphasis on the exams compared with the traditional exam-based admissions, they still place relatively greater emphasis on written examinations and other in-person assessments compared to the school recommendation admissions. Accordingly, this paper focuses on school recommendation admissions as the cleanest case of test-optional admissions.

[6] The coexistence of two types of admissions is particularly common among private universities, which account for 80% of all students. In contrast, national and public universities tend to rely more heavily on test-based admission. In this study, we therefore focus on private universities to exploit this coexistence.

[7] As an example of news article on this issue, see https://diamond.jp/articles/-/379157 (in Japanese, last accessed on December 29, 2025).

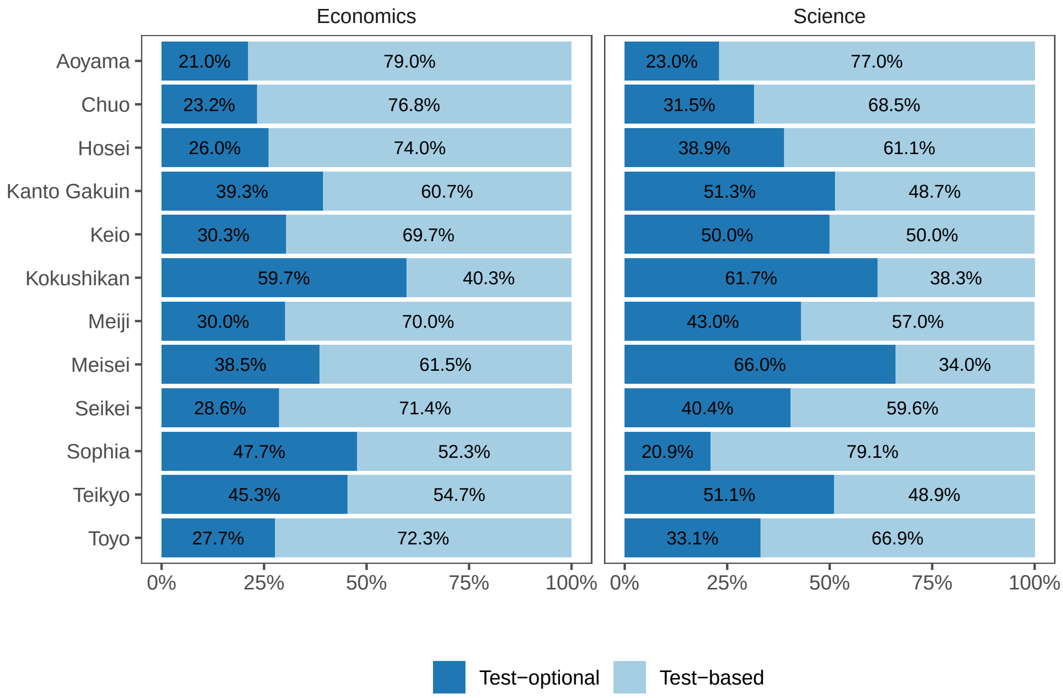

Figure 1: Co-existence of test-based and test-optional admissions among Japanese universities

Note: We show the fraction of students admitted through test-optional and test-based admissions for each school and program (=department) in our experimental design. Here, "test-optional admissions" consist of "school recommendation admissions" (*Gakkō suisen nyūshi*), while "test-based admissions" consist of the traditional test-based admissions ("general admissions" (*Ippan nyūshi*), the "holistic admissions" (*Sōgō-gata Senbatsu*, formerly known as AO admissions), and "self-recommendation admissions" (*Jiko suisen nyūshi*). See also footnote 5 for more discussions on our classification. Each row represents the name of the university, and the left side represents the economics major and the right side represents the science major. Source: Authors' own calculation based on admission information provided by each university.

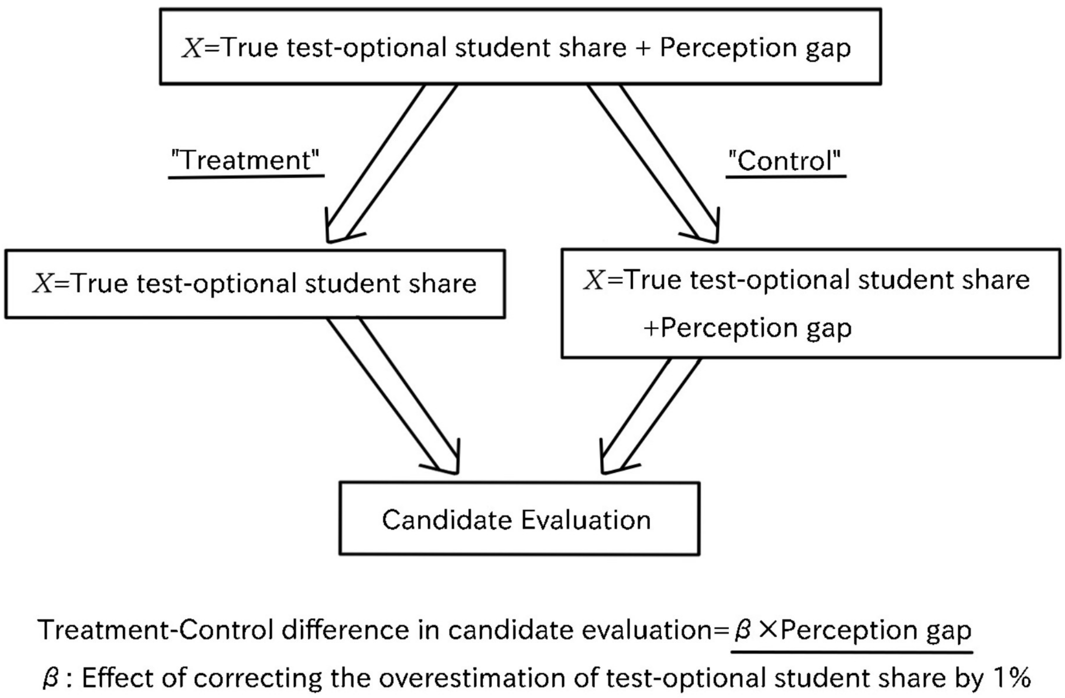

Figure 2: Visualization of the experiment

optional processes have worse performance on the job, as they may possess stronger noncognitive skills or greater motivation (Onozuka 2025). Therefore, it remains an empirical question whether employers penalize (or prefer) students admitted through test-optional admissions compared to those admitted through test-based ones.

3 Hypothesis and experimental design

Hypothesis and overview of our experimental design To facilitate understanding of our experimental design, we first lay out our hypotheses. We hypothesize that students admitted through test-optional or test-based admissions are evaluated differently in the job market. The objective of our experiment is to empirically examine whether test-optional students are rewarded or penalized in the screening process of job resumes.

A key consideration in our experimental design is that while job resumes in Japan disclose the school name and program, they do not disclose the admission system through which students were admitted. Therefore, to conduct the experiment while maintaining the natural style of Japanese job resumes, we avoided explicitly revealing and randomly manipulating whether applicants used test-optional admissions in their resumes. Instead, we exploit the fact that, for each college and program, employers possess only imperfect information about the share of students admitted through test-optional pathways. Such misperceptions are likely because test-based and test-optional admissions coexist within the same program at the same college, yet different colleges and departments allocate very different shares of seats to test-optional admissions (see Section 2).

As illustrated in Figure 2, we experimentally correct this school-program misperception on the fraction of test-optional admissions by providing the treatment group with information about the true share of test-optional admissions. More formally, let X be the "belief" of the employer about the fraction of test-optional students for a given school-program pair. This belief corresponds to the probability of drawing a test-optional student if the employer hires a student from this school-program pair. By definition, each employer's X is the sum of the true test-optional student share and the amount of misperception. Our information intervention aims to change X by correcting the misperception: X decreases if X was larger than the true fraction of test-optional students due to misperception, and vice versa. We then ask survey takers to evaluate a job resume from this school-program pair.

If employers dislike test-optional students, we expect that correcting overestimation of the fraction of test-optional students leads to higher evaluation of the job resumes, and vise versa. In contrast, if employers are indifferent between test-optional and test-based students, then our information intervention should have no effect. More formally, we can define employers' evaluation function $u(X)$ for each school and program, which reflects the utility of hiring a graduate when the perceived fraction of test-optional students is X. We expect $u(X)$ is decreasing if the employer penalizes test-optional students, increasing if the employer favors test-optional students, and independent of X if the employer is indifferent between test-optional or test-based students (see Appendix B for a more formal argument). Then, we expect that if X decreases from our intervention (i.e., the perceived fraction of test-optional students decreases), the evaluation $u(X)$ increases if and only if $u(X)$ is decreasing (i.e., the employer penalizes test-optional students). This leads to the following main hypothesis:

Hypothesis 1. *For employers who initially overestimates (underestimates) the fraction of test-optional students of a given school-program pair, informing them of the true fraction of test-optional students leads to higher (lower) evaluation if and only if they penalize test-optional students.*

Note that both the mean and the variance of the ability could be the source of penalties against test-optional students. In addition to the obvious discount against test-optional students when their average ability is lower, the variance could also matter (c.f., Neumark 2018). Intuitively, even when the average ability is the same, employers penalize test-optional students when they have the higher risk of not satisfying the minimum ability due to high noise in the test-optional admissions (see Appendix B for a more formal argument). In Appendix D.3, consistent with the institutional setting in Section 2, we find evidence suggesting that test-optional students might be considered to have both lower average and higher variance in their ability than test-based ones.

Details of the experiment We test our hypothesis using a pre-registered belief correction experiment.[8] In April 2025, we conducted a survey on a sample of employees working in human ressources for Japanese companies based in the Greater Tokyo area. We distributed the survey

[8] See https://osf.io/dwrcp for our pre-registration.

questionnaire to online panels registered with NTT Com Online, which is one of the largest Japanese online survey companies.[9] In the survey, we first asked the respondents about their prefecture of residence and the size of the firm that they are working for. Only those who work in the Greater Tokyo area and work for a private company with more than 30 employees were assigned to proceed with our survey. We also asked if the respondents had experience in personnel recruitment for their company. Participants who did not satisfy these three criteria were excluded from the sample. Survey participants were rewarded according to the rule set by the survey company. After excluding respondents who did not pass the attention check, our sample consists of 1,362 respondents.[10] Most respondents finished their survey within 15 minutes and we found little evidence of survey fatigue or insuffucient compensation affecting the answers (see Apppendix C.3 and D.2 for more details).

After answering baseline questions about their views on schooling and entrance examinations, respondents are randomly assigned to either the treatment or control group. For both groups, we ask them to evaluate five fictitious randomly-generated job applicant profiles, based on the standard profile Japanese job applicants submit for companies' entry-level hiring for new graduates. Japanese job application resumes are highly standardized in style and content, and following this format resembles the screening of actual job applications (Baron 2020; Igarashi and Mugiyama 2023). Specifically, the resume contains the following ten experimental attributes (see Appendix F for the full list), including (1) name, (2) birthdate, (3) gender, (4) current university, (5) current department, (6) academic qualifications, (7) a short personal statement, (8) extracurricular activities, (9) hobbies, and (10) possession of a driving license. A translated version of sample resume is shown in Figure 3.

Before being shown each applicant profile, both treatment and control groups are asked to give their estimate of the percentage of admissions to the applicant's university's department through school recommendation admissions (the most representative form of test-optional admissions described in Section 2) in the following way.

> What percentage of recent students admitted to University A, Department of B, do you think were admitted through "school recommendation admissions" (which consists of designated school recommendations and internal progression), rather than the general test-based admissions?

Asking the estimated fraction of test-optional students for both treatment and control groups allows us to compare treatment and control groups *conditional on* the pre-existing level of perception gap. Moreover, by exposing both groups to the context of test-optional admission, we aim to

[9] It should be noted that this survey was an opt-in survey for those who registered for the survey panel, which includes potential sample selection (American Association for Public Opinion Research 2023). However, the non-representativess of our experimental sample does not harm the internal validity and does not necessarily imply the low external validity of the identified treatment effect (Snowberg and Yariv 2021).

[10] While we originally recruited 2,626 respondents, we kept the 1,362 responses from respondents that passed the attention check in the final sample. Appendix C.4 confirms that our results are qualitatively robust to including those who did not pass the attention check.

Resume

2024/11/29

Name in Japanese alphabet	
Name	Kazuma Kato [1]
Date of birth	2002/8/2 [2]
Sex	Male [3]

Year	Month	Educational histories
2021	April	Entered Keio University [4], Department of Economics [5]
2025	March	Expected to graduate the university
		Academic achievement
		【GPA】 GPA 3.2 [6]
		【SPI exam score】 Level 3 [6]

Self-Introduction, Hobbies, Qualifications
- A short personal statement: Passionate about achieving my goals. Interested in marketing and consistently attending related seminars and study sessions. I aspire to contribute to your company's growth with this passion.[7]
- Extracurricular Activities: Film club [8]
- Hobbies: Watching sports [9]
- Qualifications: Standard driver's license [10]

Figure 3: A translated sample resume

Note: Gray scaled area represents experimented attributes. See Figure A.1 in the Appendix for the original resume sample in Japanese. See Appendix F for a full list of experimental attibutes.

mitigate the concern that experimenter demand effects drive our results (Haaland et al. 2023).[11]

After providing their estimate, *only* respondents in the treatment group are shown the true percentage of that department ' s students admitted through this type of admission, thereby correcting their belief.

> Your estimate was a%, but our calculations indicate that b% of students in recent years entered University A, Department of B through school recommendation admissions. Thus, you over/underestimated by c%.

While we derive Hypothesis 1 based on the premise that the inferred fraction of test-optional students based on the school name and the program provides a signal of students' ability, it can also hold if employers simply dislike test-optional students based on their tastes. To test the importance of its signaling value about students' ability, we further randomly sub-divide treatment and control groups into two groups: the "baseline resume" groups and "grades resume" groups. For the grades resume groups, in addition to the standard applicant profile, we display two academic qualification indicators to signal the applicant's academic ability. The first is the applicant's GPA at their university. The second is the SPI standardized score, which refers to a score derived from performance on the Synthetic Personality Inventory (SPI), a common employment aptitude test used by many Japanese private firms during the job-hunting process. We expect that the signaling value of the test-optional student share becomes smaller once employers can observe students' GPA and SPI test scores, which we empirically test in Section 4.1. However, in our main analysis, we pool the baseline resume groups and grades resume groups together to maximize statistical power.

Consistent with our expectation that people do not accurately know the prevalence of test-optional admissions for each program and school, we find that some respondents largely underestimate the actual fraction of test-optional students and others largely overestimate it. Therefore, our experimental design should induce a large correction of misperception in both directions. Figure A.2 in the Apppendix visualizes the sample distribution of the gap between respondents' estimates and the true share of test-optional students.

After seeing the resume as in Figure 3, respondents are asked to answer, on a 10-point scale, how likely the applicant is to advance to the next step of their company's recruitment process. This question serves as our outcome variable. Repeating the same procedure for different school-program combinations, we present five fictitious resumes to each respondent. Note that the treatment group is informed of the true fraction of test-optional students in all five rounds, whereas the control group is not informed in any of the rounds. After completing the evaluation of five fictitious job resumes, respondents are asked to provide answers to questions about individual demographics (e.g., gender, age, or educational background) and firm characteristics (industry, occupation, or employment practices).

[11] See Section 4.2 for more discussions on the experimetner demand effects.

Appendix D.1 reports summary statistics and balance test results, suggesting that our treatment and control groups are indeed comparable due to the successful random treatment assignment. See Appendix E for the full questionnaire.

Empirical specification We estimate the following linear model.[12] For resume k shown to respondent i:

$$Y_{ik} = \beta \text{Treatment}_i \times \text{Gap}_{ik} + \gamma_1 \text{Gap}_{ik} + \gamma_2 \text{Treatment}_i + \text{constant} + \epsilon_{ik}, \quad (1)$$

where Y_{ik} is the 10-point scale evaluation of the resume k by respondent i and Treatment_i is the treatment group dummy. $\text{Gap}_{ik} \equiv \text{Prediction Share}_{ik} - \text{True Share}_k$ is defined as the predicted share of students that used the test-optional admission system for school k minus the actual share of such students for school k.[13] If $\text{Gap}_{ik} > 0$, then our experimental treatment, informing the true fraction of test-optional students, updates downward the perceived fraction of test-optional students. The direction of the belief updating is the opposite for those with $\text{Gap}_{ik} < 0$. In this sense, Gap_{ik} can be interpreted as the exposure index to the treatment, while the sign indicates the direction of belief correction and the magnitude in absolute value represents the exposure strength to the treatment. We also include Gap_{ik} to control for any factors that are correlated with the initial level of misperceptions. Therefore, our treatment-control comparison is conditional on the initial level of the perception gap. Standard errors are clustered at the respondent level i.

Our main coefficient of interest is β, which captures the effect of perceiving 1% lower test-optional student share by correcting the overestimation. Based on Hypothesis 1, we expect $\beta > 0$ if employers dislike test-optional students because when $\beta > 0$, the treatment increases the evaluation of job resumes by correcting $\text{Gap}_{ik} > 0$, the overestimated share of test-optional students. In contrast, we expect $\beta < 0$ if employers prefer test-optional students.

As illustrated in Figure 2, we identify β by comparing survey respondents with or without the misperception correction conditional on the same initial misperception level. We implement this idea by the specification (1), where $\text{Treatment}_i \times \text{Gap}_{ik}$ captures the effect of correcting the perception gap of the test-optional student share after controlling for the initial level of perception gap (Gap_{ik}).[14] We also include the treatment dummy to control for any possible difference between the treatment and control groups that occurs regardless of the level of respondents' misperception. The overall treatment effect of our sample is $\beta\text{Gap}_{ik} + \gamma_2$. While this may appear a natural estimand of interest, γ_2 may not capture preferences for test-optional students as in Hypothesis 1

[12] We also experiment with adding quadratic terms Gap_{ik}^2 and Treatment $\times$ Gap_{ik}^2. We find that these quadratic terms are insignificant and close to zero (see Appendix C.2), suggesting that the linear specification (1) provides a good approximation.

[13] In our main analysis we do not include control variables. Appendix C.1 reports the robustness to the inclusion of control variables.

[14] We do not impose that $\gamma_1 = \beta$ because people with different levels of the misperception may be systematically different. β represents the effect of perceiving 1% lower test-optional student share, conditional on the same level of the initial misperception level.

because γ_2 is the treatment effect unrelated to the misperception correction. For example, regardless of the perceived share of test-optional students, ex post randomization, our treatment group might happen to be somewhat favorable toward test-optional students.[15] Since our interest is how our treatment affects students' job market performance through affecting the perceived share of test-optional students, we focus on reporting β, the effect of correcting misperception, in the rest of this paper.

4 Empirical Results

4.1 Main Results

We find evidence that people tend to discount the test-optional students even conditional on the same school and program. The top panel in Figure 4 presents our baseline estimate of the marginal effect of correcting 1% overestimation of the test-optional student share. We find that the coefficient is about 0.005, which is positive. This estimate corresponds to around 0.0025 standard deviation of the resume scores. Figure A.2 indicates that the gap of 40% is not rare, which leads to a 0.1 standard deviation lower score in the resume evaluation. That said, we caution that the main estimate does not exhibit statistical significance at conventional levels, although the estimate becomes statistically significant at 10% level once controlling for survey respondents' characteristics (see Appendix C.1). In our survey, many respondents express the possibility that test-optional students are inferior to test-based students in several dimensions, such as less academic preparedness for success at college and less endurance to withstand hardships (see Appendix D.3). This result is consistent with the significance of these negative evaluations of test-optional students.

Importantly, we find that the main estimate masks important heterogeneity: the test-optional students are discounted more among lower-ranked schools. The second panel in Figure 4 shows that the marginal effect of correcting 1% overestimation of the test-optional student share is larger among lower-ranked, less competitive, schools. Here, the coefficient is about 0.011 and exhibits statistical significance at 5% level. In contrast, we observe almost no effect among higher-ranked, competitive, schools. The third and fourth panels in Figure 4 confirm that this heterogeneity is not driven by the program type: engineering versus economics. Regardless of whether the program is engineering or economics, the effect is larger among the lower-ranked schools.

According to our theoretical hypothesis in Section 3, this result suggests that the test-optional students are considered as having substantially lower average ability or higher variance in their ability, but only among lower-ranked schools. One interpretation could be that test-optional admissions at higher-ranked schools are considered as competent as the test-based ones, but test-optional admissions at lower-ranked schools are considered less competent than the test-based ones. While Onozuka (2025) provides evidence that the average academic performances of students admitted through test-based and holistic admissions are similar at a middle-ranked uni-

[15] That said, reassuringly and consistently with our randomization, we find that γ_2 is insignificant in our main result.

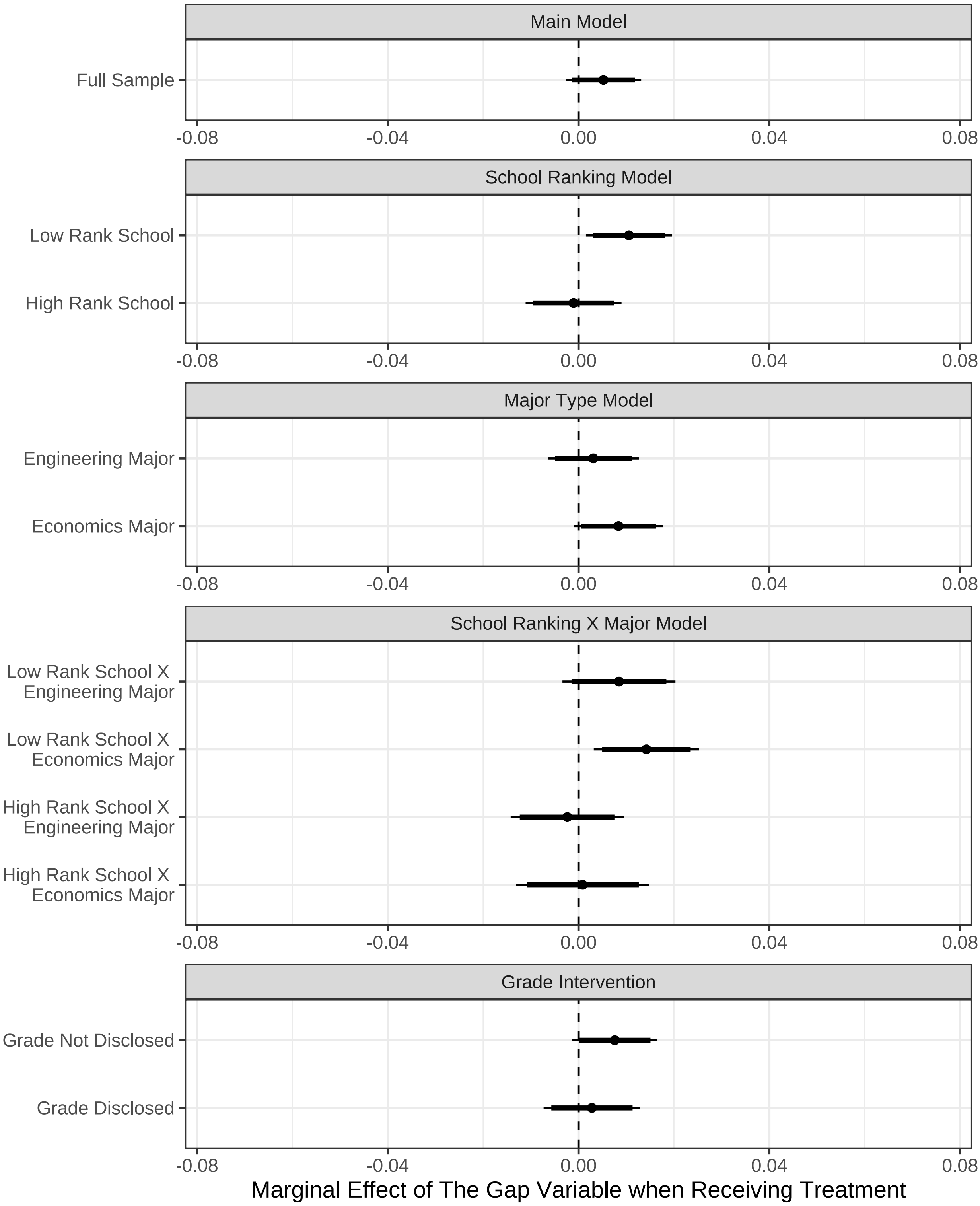

Figure 4: Main Results: Marginal effect of correcting 1% overestimation of the test-optional student share

Note: We present our estimate of β, the marginal effect of correcting 1% overestimation of the test-optional student share, in the regression model (1). As such, β captures the discount against test-optional students (see Section 3 for more details). Different rows represent different subsamples. Solid lines represent the 90% confidence intervals and the bold ones represent the 95% confidence intervals. See Tables A.1 for the full regression tables.

versity in Japan, it is still possible that firms discount students admitted through test-optional admissions to lower-ranked schools. In fact, it is possible that students admitted through holistic admissions tend to outperform those admitted through the general entrance examination in non-cognitive skills (such as communication skills) and exhibit a greater tendency to engage in self-directed learning in college. However, these high-performing and highly motivated students are, if any, concentrated in highly selective institutions (Kimura 2020; 2021). If employers believe that stronger non-cognitive skills and higher motivation for growth among students admitted through holistic admissions are characteristics found only among entrants to selective universities, they are likely to respond more strongly to the share of test-optional admissions at less selective institutions.

Another possibility is that test-optional students are viewed as exhibiting higher variance in their ability. Indeed, in our survey, many people answered that test-optional students tend to exhibit a higher variance in their ability (see Appendix D.3), suggesting the belief that test-optional admissions are more likely to students with less competent students. As argued in Section 3, this could induce the discount against test-optional students only among lower-ranked schools if firms wish to screen students satisfying the minimum ability threshold at the initial resume screening process.

Our theoretical framework in Section 3 presumes that firms engage in "statistical discrimination" in the sense that they infer the students' ability based on whether they were likely to be admitted through test-based or test-optional admissions. An alternative story is the "taste-based discrimination," in which firms dislike test-optional students and want to reject them. The taste-based discrimination does not rationalize why we observe the discount toward test-optional students only among the lower-ranked schools, making statistical discrimination more likely in our context. To further support statistical discrimination, we analyze whether the discount toward test-optional students becomes smaller once we provide additional signals: grades at college and an aptitude test score. With these information, we expect that the signaling value of test-optional admissions about students' true ability becomes relatively weaker, leading to the smaller discount when statistical discrimination is at play. At the bottom panel in Figure 4, we indeed find that the discount is larger when such additional signals are unavailable, although the difference is not statistically significant at conventional levels. This result further reinforces the relevance of statistical discrimination in our context: the use of test-optional admissions serves as a signal of students' ability in the labor market.[16]

4.2 Additional results

We report several additional results that supplement our main findings. Figure 5 summarizes the results in this section.

[16] Another evidence that limit the importance of taste-based discrimination in our context is reported in Figure 5, where we find that those who used test-optional admissions in their college entry, who may exhibit homophily with test-optional students, have as strong aversion toward test-optional students as those who used test-based admissions.

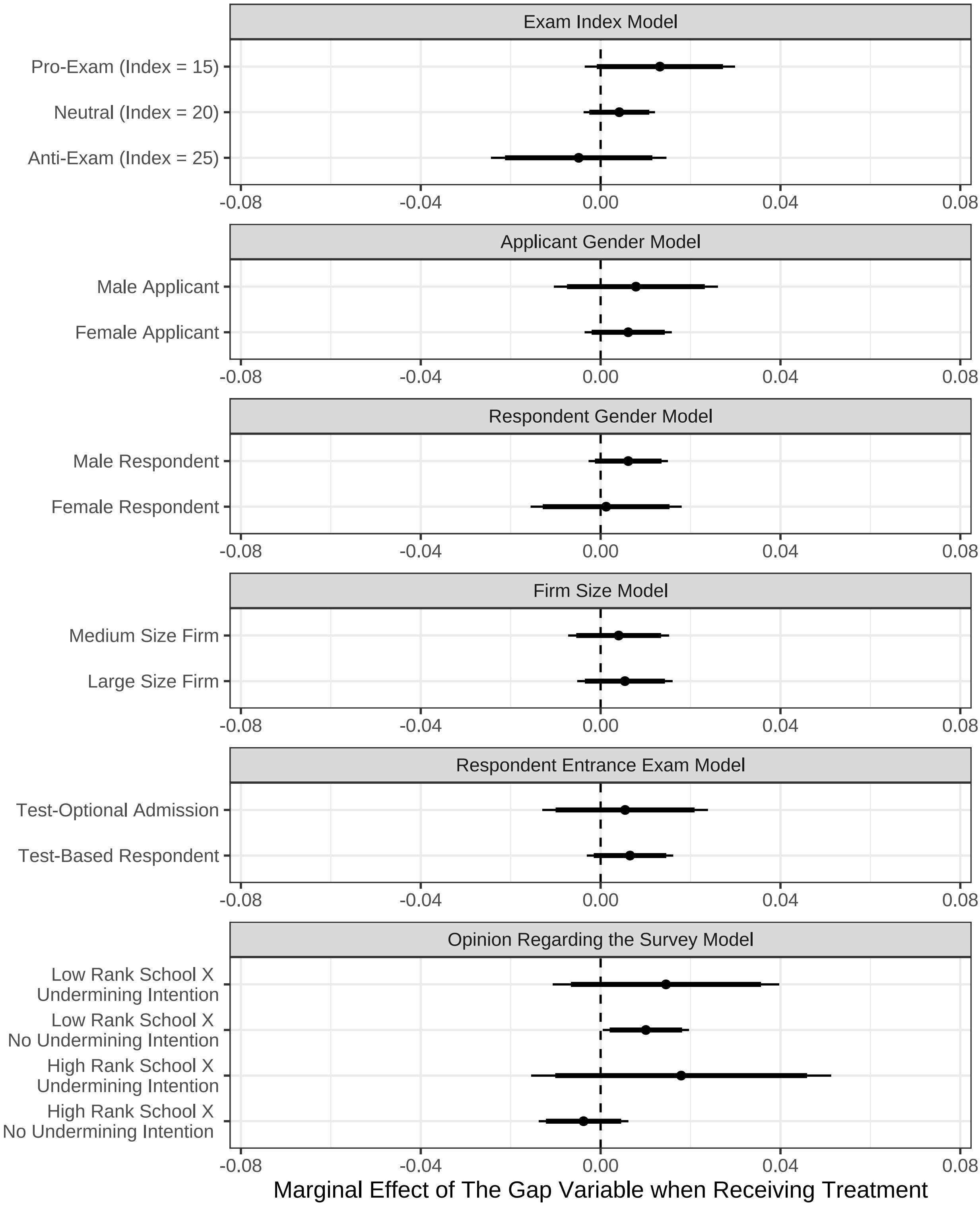

Figure 5: Additional results: Marginal effect of correcting 1% overestimation of the test-optional student share

Note: We present our estimate of β, the marginal effect of correcting 1% overestimation of the test-optional student share, in the regression model (1). β captures the discount against test-optional students (see Section 3 for more details). Different rows represent different subsamples. Solid lines represent the 90% confidence intervals and the bold ones represent the 95% confidence intervals. See Tables A.2 and A.3 for the full regression tables.

Attitudes towards entrance exams Our questionnaire elicits opinions about test-optional students, allowing us to capture individual heterogeneity in the attitudes toward test-optional students. In particular, while our analysis in Section 4.1 suggests that people, on average, discount test-optional students, some people may actually prefer test-optional students. For example, people may believe that test-optional students have, on average, better non-cognitive ability. Based on multiple survey responses, we construct a "pro-exam index" that captures how much they appreciate pro-exam students. See Appendix D.3 for more details.

Figure 5 presents how the evaluation of the test-optional student varies with our pro-exam index. We find that pro-exam respondents discount test-optional students the most. In stark contrast, anti-exam respondents actually *appreciate* test-optional students, although the statistical significance is limited. This result supports the interpretaion that our results indeed capture employers' discount against test-optional students.

Further analysis on treatment effect heterogeneity Figure 5 also explores whether the discount against test-optional students is heterogeneous in the following dimensions: (i) job applicant's gender, (ii) surrvey respondent's gender, (iii) firm size that the respondent is affliated with, and (iv) whether the respondent themselves used test-optional admissions. Overall, we find no statistically significant heterogeneity.

Assessing experimenter demand effects Our experiment is designed to minimize experimenter demand effects, which contaminates our results if our survey induces negative impressions about the test-optional students among the treatment group. First, the treatment is simply informing the *true fraction* of test-optional students, remaining neutral about stating whether it is good or bad. Second, our control group is also asked to provide their guess about the fraction of test-optional students, which mitigates the experimenter demand effect because both treatment and control groups are encourged to think about test-optional students (Haaland et al. 2023).

Our empirical results also suggest the limited importance of experimenter demand effects. First, we find the significant negative discount of test-optional students only among lower-ranked schools. However, if our results are driven by the experimenter demand effect, it is hard to consider why it operates only among the lower-ranked schools. Second, at the end of the survey, we directly ask whether our survey gave an impression that it intended to undermine students admitted through test-optional admissions. In the bottom panel of Figure 5, we find that the discount against test-optional students exist among lower-ranked schools *regardless of* whether the survey respondent felt the survey's intention of undermining test-optional students. This could suggest either (i) our main conclusion is not driven by experimenter demand effects or (ii) our survey question failed to capture experimenter demand effects. To eliminate the second possibility, we repeat the same analysis for the high-ranked schools, finding that only the survey respondents who felt we had the intention to undermine test-optional students exhibit the discount against test-optional students. This result suggests the ability of our survey question to identify survey respondents susceptible to the experimenter demand effect. Taken together, our conclusion is unlikely to be driven by experimenter demand effects.

5 Conclusion

While test-optional admissions are becoming increasingly prevalent in the United States and around the world, little is known about how they affect students' lives after graduation. This study examines how the adoption of test-optional admissions affects graduates' labor market outcomes. Using a novel online survey experiment that combines evaluations of fictitious job resumes with an information intervention about the share of test-optional students, we analyze whether test-optional graduates are discounted in the job market.

Our results show that test-optional graduates are penalized in hiring evaluations, and further evidence suggests that this penalty is driven by statistical discrimination based on perceptions of lower or more variable ability among test-optional students. We also find that the discount against test-optional graduates is particularly pronounced among those from less-selective colleges. Given that students from disadvantaged socioeconomic backgrounds are more likely to attend less-selective colleges in Japan and elsewhere, these findings suggest that test-optional policies—though often designed to promote diversity and equity—may unintentionally disadvantage such students in the job market.

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Appendix to "Test-optional Admissions and Job Market Performance: Experimental Evidence from Japan" (Not for Publication)

A Omitted Figures and Tables

Here we collect all figures and tables that are mentioned in the main text but do not belong to any other Appendix sections.

A.1 Omitted Figures

履歴書

2024 年 11 月 29 日現在

ふりがな　かとう　かずま	
氏名　加藤一真	
2002 年　8 月　2 日生　(満　22　歳)	性別 男性

年	月	学 歴・成　績
2021	4 月	慶應義塾大学 経済学部 入学
2025	3 月	慶應義塾大学 経済学部 卒業見込み
		成績
		【GPA】 GPA 3.2
		【SPI 偏差値】段階 3

自己 PR、趣味、資格など

【自己 PR】　私は自分の目標に対して常に情熱を持って取り組んでいます。特にマーケティングに興味があり、関連するセミナーや勉強会に参加し続けています。この情熱をもって、御社の成長に寄与したいと考えています。

【課外活動】　映画サークル

【趣味】　スポーツ観戦

【資格】　普通自動車第一種運転免許

Figure A.1: A Japanese version of sample resume

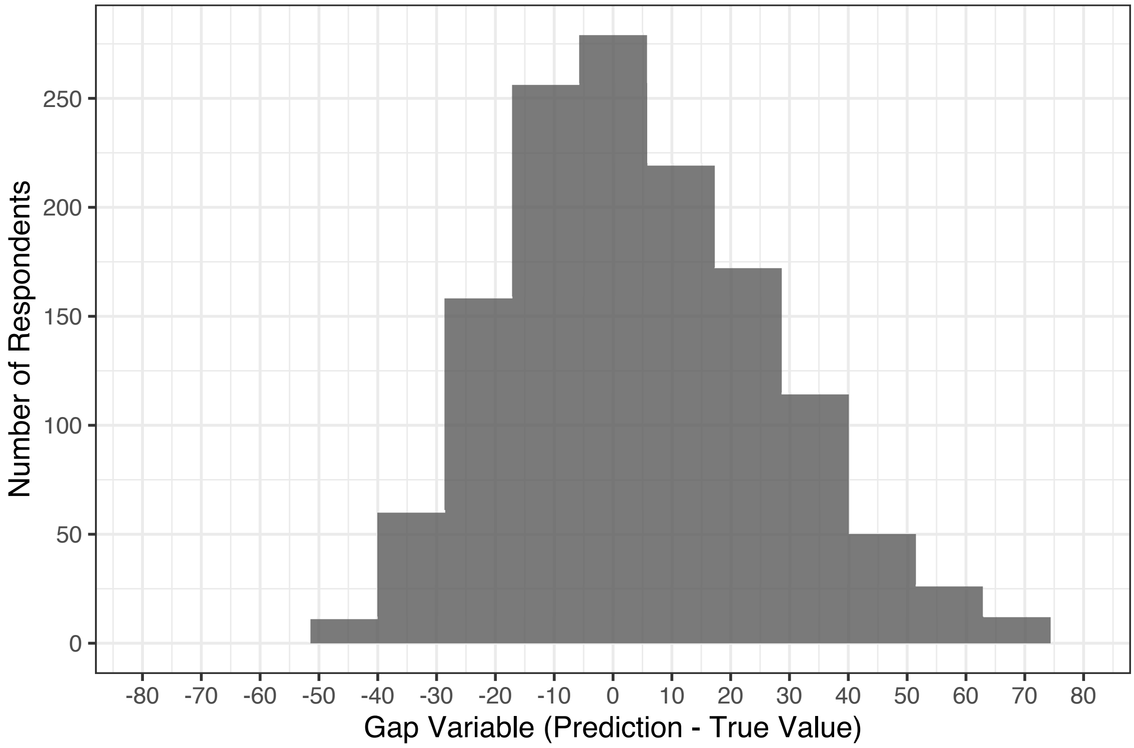

Figure A.2: Histogram of the gap between predictions and true values across the whole sample.

A.2 Omitted Tables

	Pooled Treatment Arms	Grade Intervention	School Ranking	Major Type
Intercept	5.527***	5.543***	5.188***	5.475***
	(0.064)	(0.074)	(0.072)	(0.070)
Treatment	0.120	0.073	0.056	0.233**
	(0.090)	(0.105)	(0.104)	(0.100)
Gap	−0.002	−0.005*	−0.004	−0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment x Gap	0.005	0.008*	0.011**	0.008*
	(0.004)	(0.005)	(0.005)	(0.005)
Grade Disclosure		−0.032		
		(0.072)		
Gap x Grade Disclosure		0.006*		
		(0.003)		
Treatment x Grade Disclosure		0.093		
		(0.101)		
Treatment x Gap x Grade Disclosure		−0.005		
		(0.005)		
High Rank School			0.675***	
			(0.076)	
Treatment x High Rank School			0.140	
			(0.110)	
Gap x High Rank School			0.006*	
			(0.003)	
Treatment x Gap x High Rank School			−0.012**	
			(0.006)	
Science Major				0.110
				(0.074)
Treatment x Science Major				−0.229**
				(0.105)
Gap x Science Major				−0.002
				(0.003)
Treatment x Gap x Science Major				−0.005
				(0.005)
Std.Errors Clustered:	Respondent	Respondent	Respondent	Respondent
Num.Obs.	6810	6810	6810	6810
R2	0.002	0.002	0.036	0.003

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.1: Full regression tables for the models used to produce the coefficient plots in Figure 4

	Profile Gender	Respondent Gender	Exam Index
Intercept	5.660***	5.504***	5.748***
	(0.119)	(0.072)	(0.498)
Treatment	−0.299*	0.169*	0.013
	(0.174)	(0.101)	(0.678)
Gap	−0.001	−0.004	−0.037*
	(0.005)	(0.003)	(0.021)
Treatment x Gap	0.008	0.006	0.040
	(0.009)	(0.005)	(0.033)
Exam Index			−0.011
			(0.025)
Treatment x Exam Index			0.006
			(0.033)
Treatment x Gap x Exam Index			−0.002
			(0.002)
Female Respondent		0.149	
		(0.150)	
Treatment x Female Respondent		−0.326	
		(0.222)	
Treatment x Gap x Female Respondent		−0.005	
		(0.010)	
Female Profile	−0.089		
	(0.066)		
Treatment x Female Profile	0.280***		
	(0.101)		
Treatment x Gap x Female Profile	−0.002		
	(0.006)		
Num.Obs.	6810	6810	6345
Std.Errors Clustered:	Respondent	Respondent	Respondent
R2	0.003	0.003	0.004

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Regression table for the interaction coefficients shown in Figure 5 (Part 1)

	Size of Firm	Respondent Exam Type	Respondent Perception
Intercept	5.686***	5.575***	5.170***
	(0.099)	(0.132)	(0.077)
Treatment	−0.005	−0.039	0.020
	(0.141)	(0.202)	(0.111)
Gap	−0.003	−0.007	−0.004
	(0.004)	(0.005)	(0.003)
Treatment x Gap	0.004	0.005	0.010**
	(0.006)	(0.009)	(0.005)
High Rank School			0.654***
			(0.080)
Treatment x High Rank School			0.189
			(0.116)
Gap x High Rank School			0.006
			(0.004)
Treatment x Gap x High Rank School			−0.014**
			(0.006)
Large Firm	−0.257**		
	(0.129)		
Gap x Large Firm	0.001		
	(0.005)		
Treatment x Gap x Large Firm	0.001		
	(0.008)		
Undermining Intention			0.159
			(0.240)
Treatment x Undermining Intention			0.306
			(0.322)
Exam-Based Admission		−0.102	
		(0.155)	
Treatment x Exam-Based Admission		0.108	
		(0.231)	
Treatment x Gap x Exam-Based Admission		0.001	
		(0.011)	
Std.Errors Clustered:	Respondent	Respondent	Respondent
Num.Obs.	6810	5690	6810
R2	0.004	0.003	0.040

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Regression table for the models used to produce the coefficient plot shown in Figure 5 (part 2)

B Mean and variance of test-optional students' ability and the discount against test-optional students

To illustrate our argument in Section 3 that the mean and variance of test-optional students' ability could be a source of statistical discrimination against them, suppose that employers seek workers who meet a minimum ability requirement: an employer receives utility 1 if the ability exceeds $\underline{a}$ and receives 0 otherwise. Suppose also that the ability of test-optional students follows the normal distribution $N(a_{TO}, \sigma_{TO})$, and we denote by $F(\underline{a}; a_{TO}, \sigma_{TO})$ the probability that the test-optional students' ability exceeds the minimum requirement $\underline{a}$ when the mean is a_{TO} and the variance is σ_{TO}. Analogously, let $F(\underline{a}; a_{TB}, \sigma_{TB})$ be the probability that the ability of test-based students surpasses the minimum requirement $\underline{a}$.

Then, the evaluation function of job applications when the perceived fraction of test-optional students X is written as the expected value: $u(X) = XF(\underline{a}; a_{TO}, \sigma_{TO}) + (1 - X)F(\underline{a}; a_{TB}, \sigma_{TB})$. Here, $u(X)$ is decreasing if and only if $F(\underline{a}; a_{TO}, \sigma_{TO}) < F(\underline{a}; a_{TB}, \sigma_{TB})$. Note that when $F(\underline{a}; a_{TO}, \sigma_{TO}) < F(\underline{a}; a_{TB}, \sigma_{TB})$ holds, employers prefer test-based students over test-optional ones.

$F(\underline{a}; a_{TO}, \sigma_{TO}) < F(\underline{a}; a_{TB}, \sigma_{TB})$ is likely to hold when $a_{TO} < a_{TB}$ so that test-optional students' ability is, on average, lower. Moreover, even when the average ability is the same (i.e., $a_{TO} = a_{TB}$), the inequality holds if $\sigma_{TO} > \sigma_{TB}$ and $\underline{a} < a_{TO} = a_{TB}$.[B.1] In this sense, both lower average ability and high variance of test-optional students' ability could be a source of discount against them.

[B.1] However, when $\bar{a}$ is substantially smaller than the average ability $a_{TO} = a_{TB}$, $F(\underline{a}; a_{TO}, \sigma_{TO})$ and $F(\underline{a}; a_{TO}, \sigma_{TO})$ are nearly identical because both are sufficiently close to one. This is consistent with our result that test-optional students of lower-ranked schools are penalized but those of high-ranked schools are not.

C Alternative specifications

C.1 Regressions with control variables

We estimate several models that include control variables. This includes specifications that control for 1) The other characteristics that were randomly assigned to job applicants (Extracurriculurs, gender, etc.; see Figure 3), 2) Respondent characteristics (e.g. respondent gender, company size, etc.). We estimate the model using three different sets of control variables. The control variables included in each set are as follows:

- **Set 1 (Table C.1):** Candidate's Faculty, Candidate's Gender, Candidate's Extracurricular Activities, Candidate's Qualifications, Candidate's Hobbies.
- **Set 2 (Table C.2):** Respondent Age, Respondent Gender, Prefecture of residence, Company size, Most hired job type, Job title, Respondent Industry, Highest level of education.
- **Set 3 (Table C.3):** Respondent Age, Respondent Gender, Prefecture of residence, Company size, Most hired job type, Job title, Respondent Industry, Highest level of education, Field of study, University entrance method

Based on these regression results, in Figures C.1–C.3 we reproduce our main coefficient plot (Figure 4). Figure C.1 is based on Table C.1, Figure C.2 is based on Table C.2, and Figure C.3 is based on Table C.3.

	Pooled Treatment Arms	Grade Intervention	School Ranking	Major Type
Intercept	5.132***	5.158***	4.812***	5.071***
	(0.136)	(0.143)	(0.139)	(0.139)
Treatment	0.120	0.070	0.054	0.225**
	(0.090)	(0.105)	(0.104)	(0.099)
Gap	−0.002	−0.006*	−0.004	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment x Gap	0.005	0.008*	0.011**	0.008*
	(0.004)	(0.005)	(0.005)	(0.005)
Grade Disclosure		−0.042		
		(0.072)		
Gap x Grade Disclosure		0.006**		
		(0.003)		
Treatment x Grade Disclosure		0.099		
		(0.101)		
Treatment x Gap x Grade Disclosure		−0.005		
		(0.005)		
High Rank School			0.664***	
			(0.076)	
Treatment x High Rank School			0.145	
			(0.110)	
Gap x High Rank School			0.006*	
			(0.003)	
Treatment x Gap x High Rank School			−0.012**	
			(0.006)	
Science Major				0.106
				(0.074)
Treatment × Science Major				−0.213**
				(0.104)
Gap × Science Major				−0.002
				(0.003)
Treatment × Gap × Science Major				−0.005
				(0.005)
Std.Errors Clustered:	Respondent	Respondent	Respondent	Respondent
Num.Obs.	6810	6810	6810	6810
R2	0.015	0.016	0.049	0.016
Controls:	Set 1	Set 1	Set 1	Set 1

* p < 0.1, ** p < 0.05, *** p < 0.001

Table C.1: Main model estimated with our first set of control variables.

	Pooled Treatment Arms	Grade Intervention	School Ranking	Major Type
Intercept	9.559***	9.450***	9.451***	9.506***
	(1.346)	(1.335)	(1.358)	(1.352)
Treatment	0.103	0.046	0.020	0.221**
	(0.090)	(0.104)	(0.101)	(0.099)
Gap	−0.003	−0.006**	−0.004	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment x Gap	0.007*	0.009**	0.011**	0.009**
	(0.004)	(0.004)	(0.004)	(0.005)
Grade Disclosure		−0.032		
		(0.071)		
Gap x Grade Disclosure		0.005*		
		(0.003)		
Treatment x Grade Disclosure		0.112		
		(0.099)		
Treatment x Gap x Grade Disclosure		−0.005		
		(0.005)		
High Rank School			0.662***	
			(0.075)	
Treatment x High Rank School			0.181*	
			(0.108)	
Gap x High Rank School			0.004	
			(0.003)	
Treatment x Gap x High Rank School			−0.009	
			(0.005)	
Science Major				0.126*
				(0.073)
Treatment × Science Major				−0.241**
				(0.103)
Gap × Science Major				−0.001
				(0.003)
Treatment × Gap × Science Major				−0.004
				(0.005)
Std.Errors Clustered:	Respondent	Respondent	Respondent	Respondent
Num.Obs.	6810	6810	6810	6810
R2	0.055	0.055	0.089	0.056
Controls:	Set 2	Set 2	Set 2	Set 2

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table C.2: Main model estimated with our second set of control variables.

	Pooled Treatment Arms	Grade Intervention	School Ranking	Major Type
Intercept	4.473***	4.490***	4.469***	4.314***
	(0.596)	(0.599)	(0.583)	(0.597)
Treatment	0.052	−0.027	−0.017	0.212**
	(0.098)	(0.113)	(0.113)	(0.107)
Gap	−0.006**	−0.009**	−0.006*	−0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment x Gap	0.008*	0.013**	0.010**	0.011**
	(0.004)	(0.005)	(0.005)	(0.005)
Grade Disclosure		−0.092		
		(0.076)		
Gap x Grade Disclosure		0.007*		
		(0.003)		
Treatment x Grade Disclosure		0.153		
		(0.106)		
Treatment x Gap x Grade Disclosure		−0.011*		
		(0.005)		
High Rank School			0.749***	
			(0.080)	
Treatment x High Rank School			0.159	
			(0.119)	
Gap x High Rank School			0.004	
			(0.004)	
Treatment x Gap x High Rank School			−0.005	
			(0.006)	
Science Major				0.207**
				(0.078)
Treatment × Science Major				−0.322**
				(0.112)
Gap × Science Major				0.000
				(0.003)
Treatment × Gap × Science Major				−0.005
				(0.006)
Std.Errors Clustered:	Respondent	Respondent	Respondent	Respondent
Num.Obs.	5690	5690	5690	5690
R2	0.065	0.066	0.106	0.067
Controls:	Set 3	Set 3	Set 3	Set 3

* p < 0.1, ** p < 0.05, *** p < 0.001

Table C.3: Main model estimated with our third set of control variables.

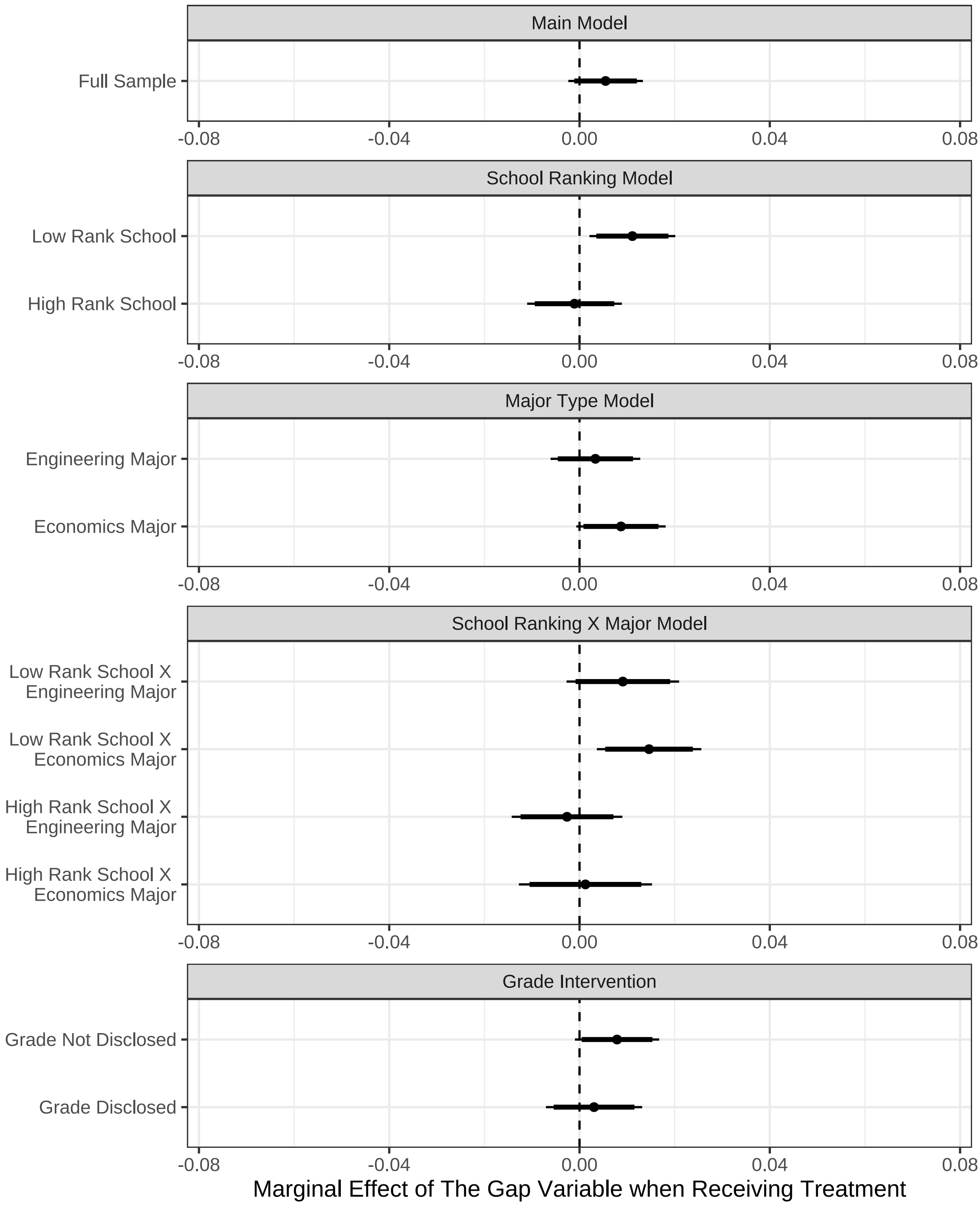

Figure C.1: Additional results: Marginal effect of correcting 1% overestimation of the test-optional student share in models using the first set of control variables

Note: We present our estimate of β, the marginal effect of correcting 1% overestimation of the test-optional student share, in the regression model (1). As such, β captures the discount against test-optional students (see Section 3 for more details). Different rows represent different subsamples. Solid lines represent the 90% confidence intervals and the bold ones represent the 95% confidence intervals. We control for variables specified in Appendix C.1. See Tables C.1 for the corresponding full regression tables.

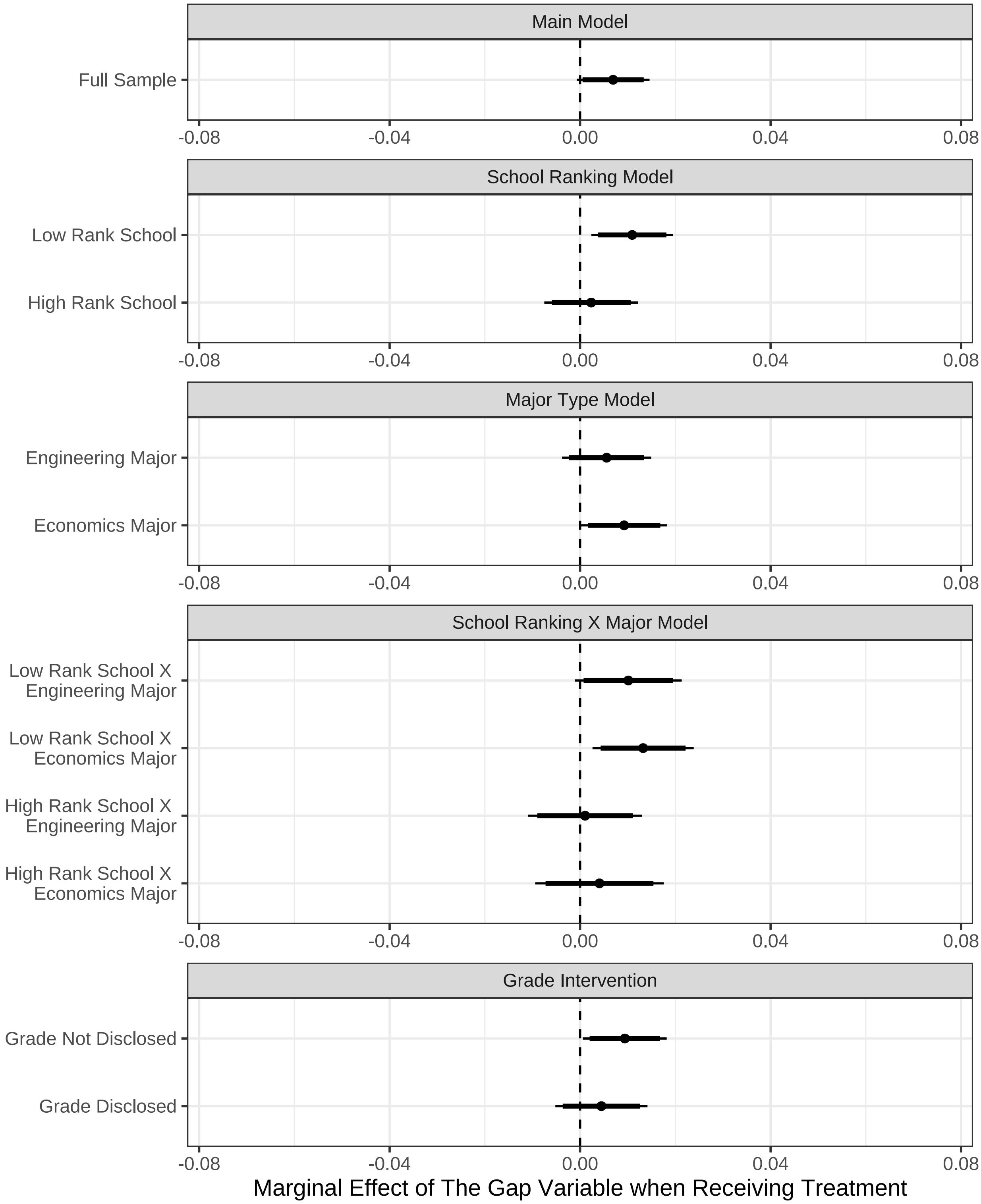

Figure C.2: Additional results: Marginal effect of correcting 1% overestimation of the test-optional student share in models using the second set of control variables

Note: We present our estimate of β, the marginal effect of correcting 1% overestimation of the test-optional student share, in the regression model (1). As such, β captures the discount against test-optional students (see Section 3 for more details). Different rows represent different subsamples. Solid lines represent the 90% confidence intervals and the bold ones represent the 95% confidence intervals. We control for variables specified in Appendix C.1. See Tables C.2 for the corresponding full regression tables.

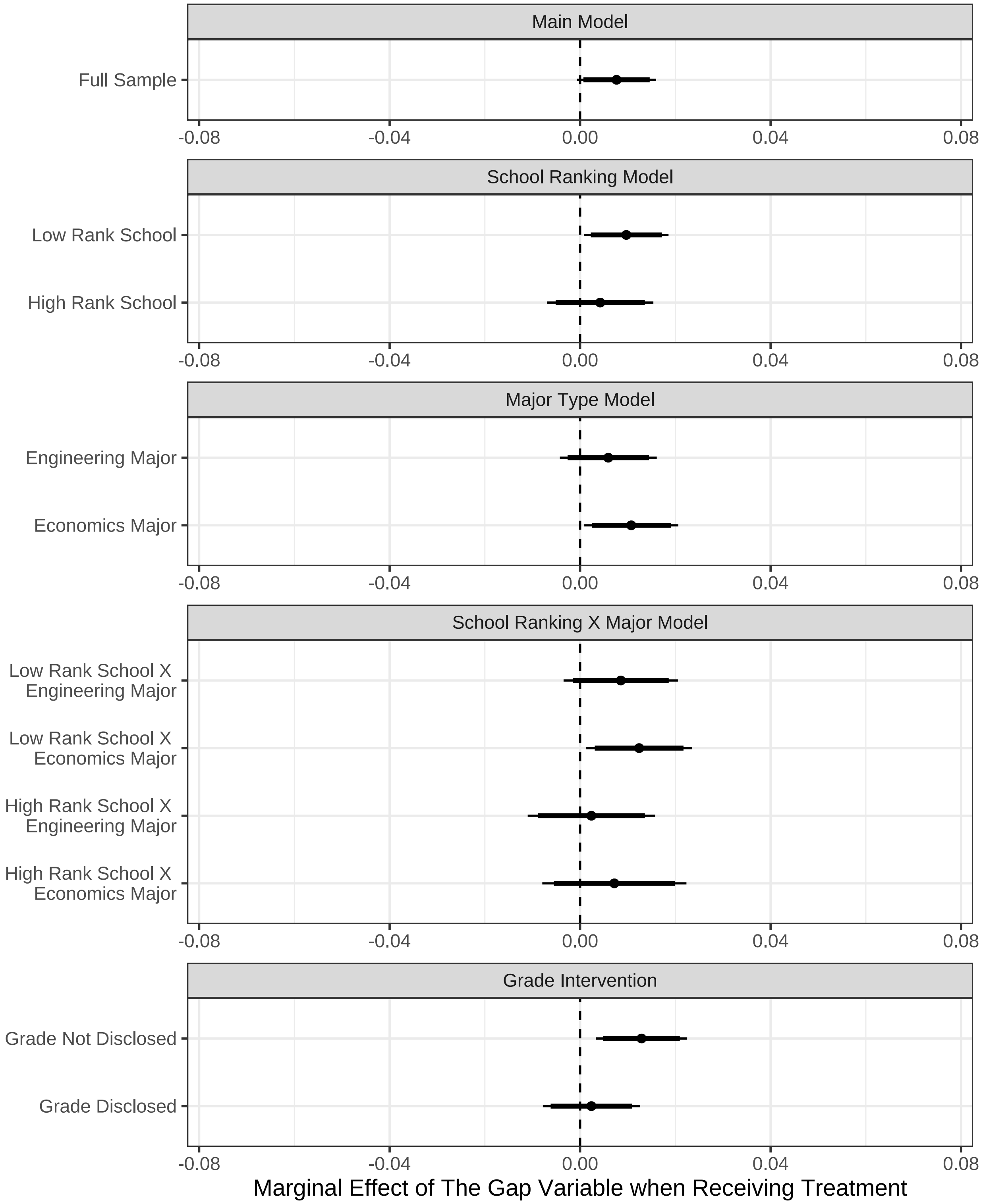

Figure C.3: Additional results: Marginal effect of correcting 1% overestimation of the test-optional student share in models using the third set of control variables

Note: We present our estimate of β, the marginal effect of correcting 1% overestimation of the test-optional student share, in the regression model (1). As such, β captures the discount against test-optional students (see Section 3 for more details). Different rows represent different subsamples. Solid lines represent the 90% confidence intervals and the bold ones represent the 95% confidence intervals. We control for variables specified in Appendix C.1. See Tables C.3 for the corresponding full regression tables.

C.2 Non-Linear Effects

We test for non-linear effects of the gap variable by adding a second-degree polynomial term of the gap variable to our main specifications. We do not find significant coefficients for any of the second-degree expansion: We do not find an important non-linear relationship between the level of misperception and the effect of the information correction treatment. We conclude that the linear additive interaction term used in the main body of the paper is a good enough approximation of the data generating process. Results are shown in Table C.4.

	(1)	(2)	(3)	(4)
Intercept	5.5086***	5.1960***	5.4553***	5.5536***
	(0.0694)	(0.0795)	(0.0818)	(0.0838)
Treatment	0.1070	0.0336	0.2821**	0.0322
	(0.0994)	(0.1171)	(0.1145)	(0.1169)
Gap	−0.0031	−0.0032	−0.0024	−0.0048
	(0.0029)	(0.0034)	(0.0034)	(0.0034)
Treatment x Gap	0.0045	0.0094**	0.0106**	0.0059
	(0.0039)	(0.0048)	(0.0049)	(0.0049)
Grade Disclosure				−0.0850
				(0.0831)
Gap x Grade Disclosure				0.0035
				(0.0038)
Treatment x Grade Disclosure				0.1449
				(0.1165)
Treatment x Gap x Grade Disclosure				−0.0028
				(0.0061)
High Rank School		0.6086***		
		(0.0864)		
Treatment x High Rank School		0.1659		
		(0.1248)		
Gap x High Rank School		0.0031		
		(0.0039)		
Treatment x Gap x High Rank School		−0.0105*		
		(0.0061)		
Science Major			0.1114	
			(0.0868)	
Treatment × Science Major			−0.3359***	
			(0.1213)	
Gap × Science Major			−0.0018	
			(0.0036)	
Treatment × Gap × Science Major			−0.0103*	
			(0.0059)	
Gap^2	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Treatment x Gap^2	0.0001	0.0001	−0.0002	0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
High Rank School x Gap^2		0.0001		
		(0.0001)		
Treatment x High Rank School x Gap^2		0.0000		
		(0.0002)		
Grade Disclosure x Gap^2				0.0001
				(0.0001)
Treatment x Grade Disclosure x Gap^2				−0.0001
				(0.0002)
Num.Obs.	6810	6810	6810	6810
R2	0.002	0.038	0.005	0.003

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Main model specification with a second degree polynomial expansion of the gap variable.

C.3 Survey Fatigue and Satisficing

In our survey we asked respondents whether they felt like the survey was too long and they lost focus at the end or whether they felt like the payment offered was insufficient. We drop respondents who answered yes to either of these questions to make sure that satisficing behavior from those respondents did not drive our results. The main models' interaction coefficients when excluding those respondents are reported in Figure C.4. In general, all results are directionally similar when including these repondents, mitigating the concern of survey fatigue and insufficient compensation.

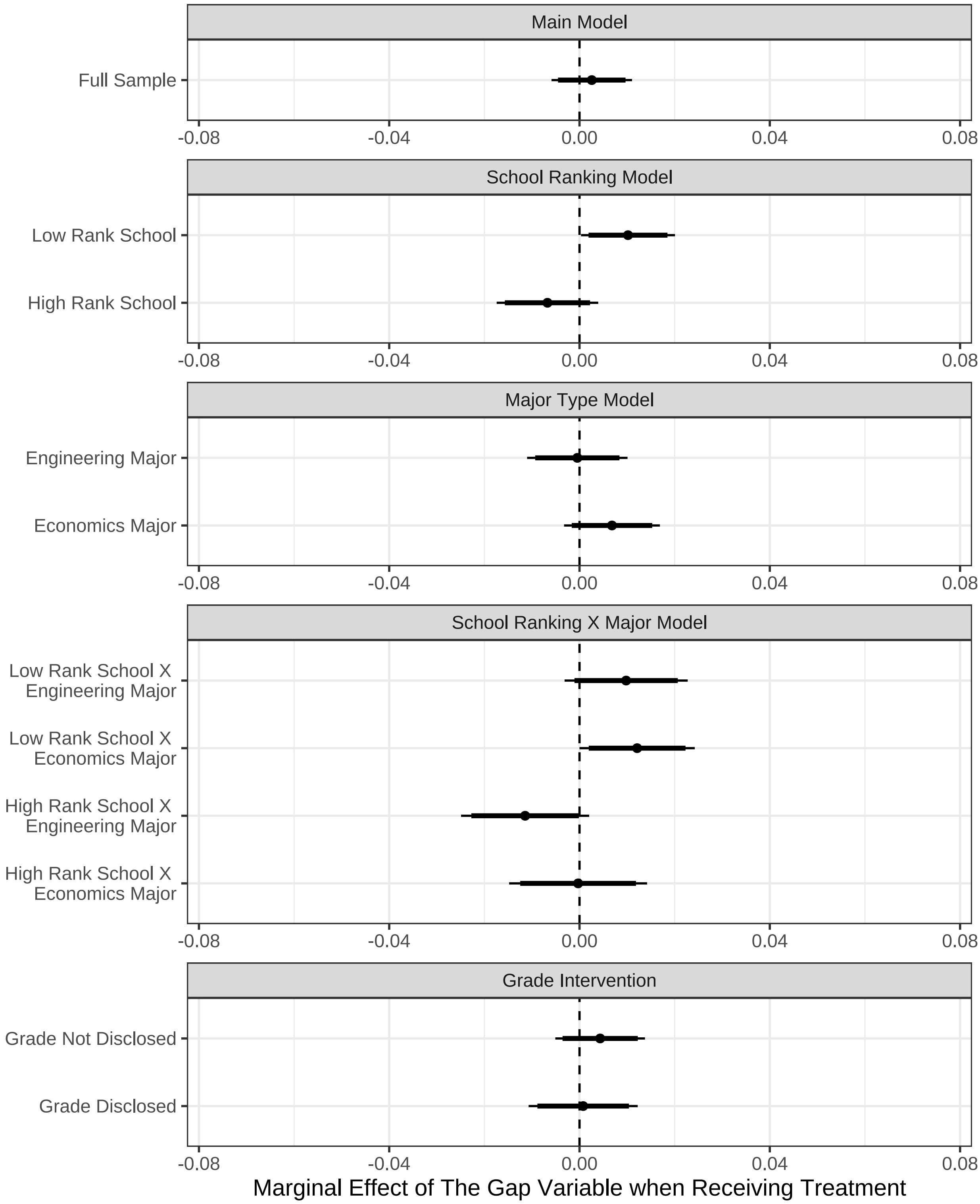

Figure C.4: Coefficient plot of main models when removing respondents who felt like they were compensated too poorly or that the survey was too long.

C.4 Attention Check

Our survey included a simple attention check where respondents had to answer a multiple choice questions where they were instructed to select three specific choices out of six possible options (see Question 6 of our questionnaire in Appendix E for details). From all the respondents recruited by the survey firm, 48% failed the task. Respondents who failed this simple attention check were excluded from the main analysis. We reproduce the main coefficient plot from Figure 4 when including these respondents in Figure C.5. In general, all results are directionally similar when including these repondents but the effect size is attenuated, which is as expected.

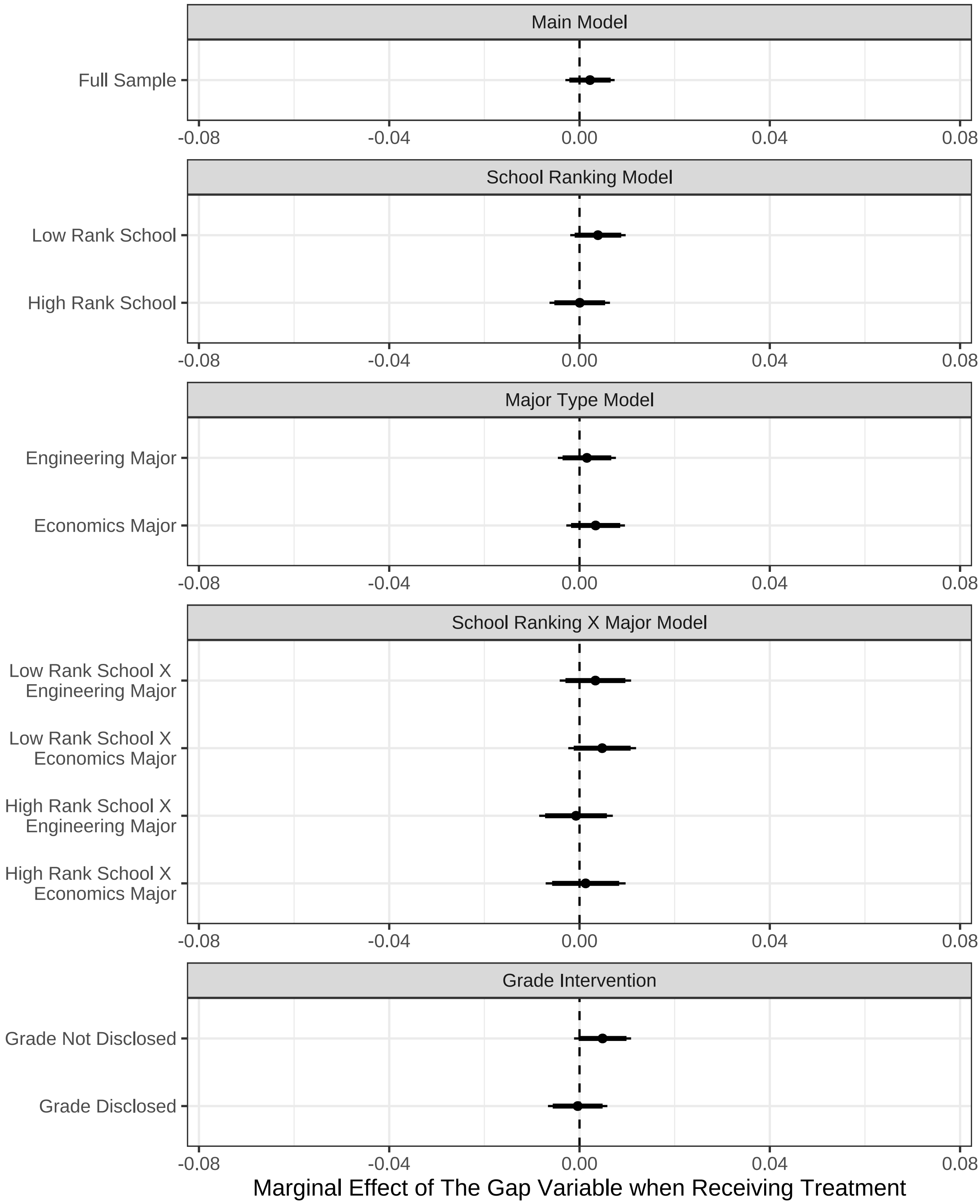

Figure C.5: Coefficient plot of the results when including respondents that failed our attention check.

D Data details

D.1 Summary statistics and balance tests

We provide the mean of each variable, separately for control and treatment groups. We conduct t-tests of the difference in means between the treatment and control group for various respondent-level characteristics that were measured as part of our survey. The results are reported in table D.1. Overall we find that our treatment and control groups are balanced: We find few statistically-significant differences between respondent characteristics of the treatment and control group.

Variable	Mean Control	Mean Treat	p value
Age	50.76	51.215	0.26
Male	0.84	0.847	0.90
Non-metropolitan origin	0.30	0.31	0.54
Position: Supervisor / Team Leader	0.06	0.05	0.46
Position: Section Chief or Equivalent	0.13	0.099**	0.01
Position: Division Chief or Equivalent	0.28	0.278	0.85
Position: Department Head or Equivalent	0.28	0.297	0.36
Position: Executive / Director / Officer	0.10	0.121	0.09
Position: Other	0.02	0.02	1.00
Industry: Professional, Technical Services	0.05	0.04	0.13
Industry: Medical, Welfare	0.06	0.054	0.57
Industry: Education, Learning Support	0.03	0.027	0.93
Industry: Accommodation, Food, Entertainment	0.04	0.039	0.59
Industry: Other Services	0.12	0.121	0.82
Industry: Public Service	0.00	0.004	0.56
Industry: Other	0.04	0.029	0.29
Industry: Mining, Quarrying, Construction	0.04	0.031	0.09
Industry: Manufacturing	0.21	0.224	0.30
Industry: Electricity, Gas, Water Supply	0.01	0.02	0.22
Industry: Information, Media	0.11	0.123	0.38
Industry: Transport, Postal	0.04	0.06	0.09
Industry: Wholesale, Retail	0.10	0.103	0.94
Industry: Finance, Insurance	0.09	0.085	0.88
Industry: Real Estate, Leasing	0.05	0.037	0.24
Last School: High School	0.09	0.1	0.30
Last School: Vocational School (after High School)	0.07	0.08	0.40
Last School: Junior College	0.03	0.013**	0.00
Last School: College of Technology (Kosen)	0.02	0.015	0.25

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Table D.1 – continued from previous page

Variable	Mean Control	Mean Treat	p value
Last School: Four-Year University	0.68	0.7	0.36
Last School: Six-Year University (Medical/Dental/Pharmacy)	0.01	0.008	0.62
Last School: Graduate School	0.09	0.083	0.48
School Major: Humanities	0.13	0.115	0.29
School Major: Other	0.17	0.2	0.06
School Major: Social Sciences	0.19	0.212	0.24
School Major: Natural Sciences	0.06	0.061	0.81
School Major: Engineering	0.18	0.142**	0.01
School Major: Agriculture	0.01	0.022*	0.02
School Major: Medicine/Dentistry	0.01	0.01	0.63
School Major: Pharmacy	0.01	0.008	0.38
School Major: Education	0.03	0.028	0.69
School Major: Home Economics	0.01	0.004	0.08
University Admission: General Entrance Exam	0.60	0.616	0.38
University Admission: Open Recommendation	0.04	0.031	0.10
University Admission: AO Entrance Exam (Comprehensive)	0.02	0.022	0.78
University Admission: Designated School Recommendation	0.07	0.061	0.27
University Admission: Advancement from Affiliated School	0.06	0.053	0.33
University Admission: Other	0.01	0.013	0.80
University Admission: No Entrance Exam	0.00	0.007*	0.01
Prefecture: Gunma	0.00	0.001	0.30
Prefecture: Saitama	0.17	0.163	0.68
Prefecture: Chiba	0.14	0.141	0.92
Prefecture: Tokyo	0.46	0.447	0.70
Prefecture: Kanagawa	0.23	0.248	0.35
Prefecture: Tochigi	0.00	0.001	0.32
Company Size: 100-299 People	0.20	0.191	0.51
Company Size: 300-999 People	0.20	0.197	0.90
Company Size: >1000 People	0.40	0.406	0.85
Company Size: Don't Know	0.01	0.009	0.18
Most Recruited Position: Delivery	0.03	0.022	0.60
Most Recruited Position: Agriculture	0.00	0.004	0.27
Most Recruited Position: Other	0.06	0.057	0.95
Most Recruited Position: Management	0.20	0.212	0.30
Most Recruited Position: Office Job	0.19	0.182	0.77
Most Recruited Position: Sales	0.16	0.135	0.10
Most Recruited Position: Service Job	0.07	0.06	0.18

Continued on next page

Table D.1 – continued from previous page

Variable	Mean Control	Mean Treat	p value
Most Recruited Position: Security	0.01	0.01	0.64
Most Recruited Position: Factory Job	0.06	0.079*	0.05
Most Recruited Position: Driver/Pilot	0.01	0.025	0.05
Most Recruited Position: Construction	0.03	0.018	0.11
Attention Check	0.52	0.518	0.97

Table D.1: Balance table between respondent characteristics in both the treatment and control group. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D.2 Response Time

In figure D.1, we show a histogram of the total amount of time spent answering the survey in both the control and the treatment group. We do not find important differences by treatment status in the amount of time spent answering the survey.

To address the possibility that our survey induced survey fatigue, we ask at the end of the survey two questions. First, we asked whether the respondents felt "the reward was too low compared to the length of the survey." Second, we asked whether the respondents felt "he similar questions continued for too long, and I got tired and answered randomly towards the end." 23% people answered yes to either of these questions. Dropping those respondents does not change our results. We report the main interaction coefficients when dropping those respondents in figure C.4. We also estimate the main specifications using only respondents that spent more than 5 minutes answering our survey. The results are reported in figure D.2.

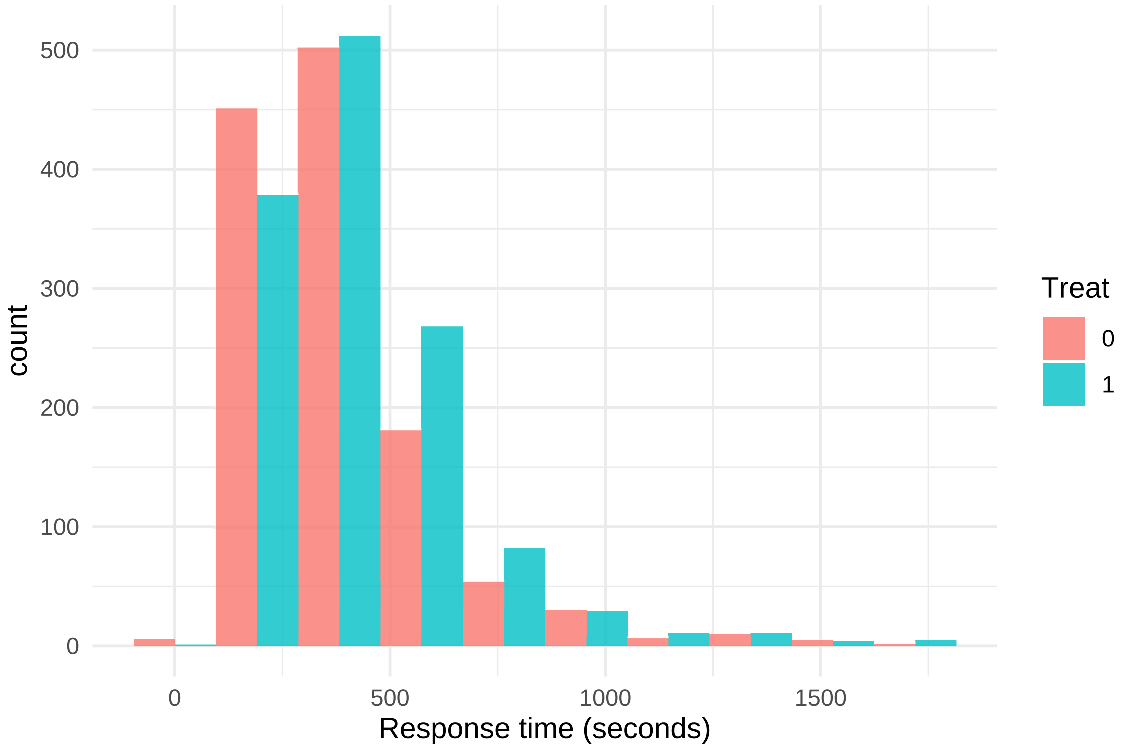

Figure D.1: Response time in each treatment group.

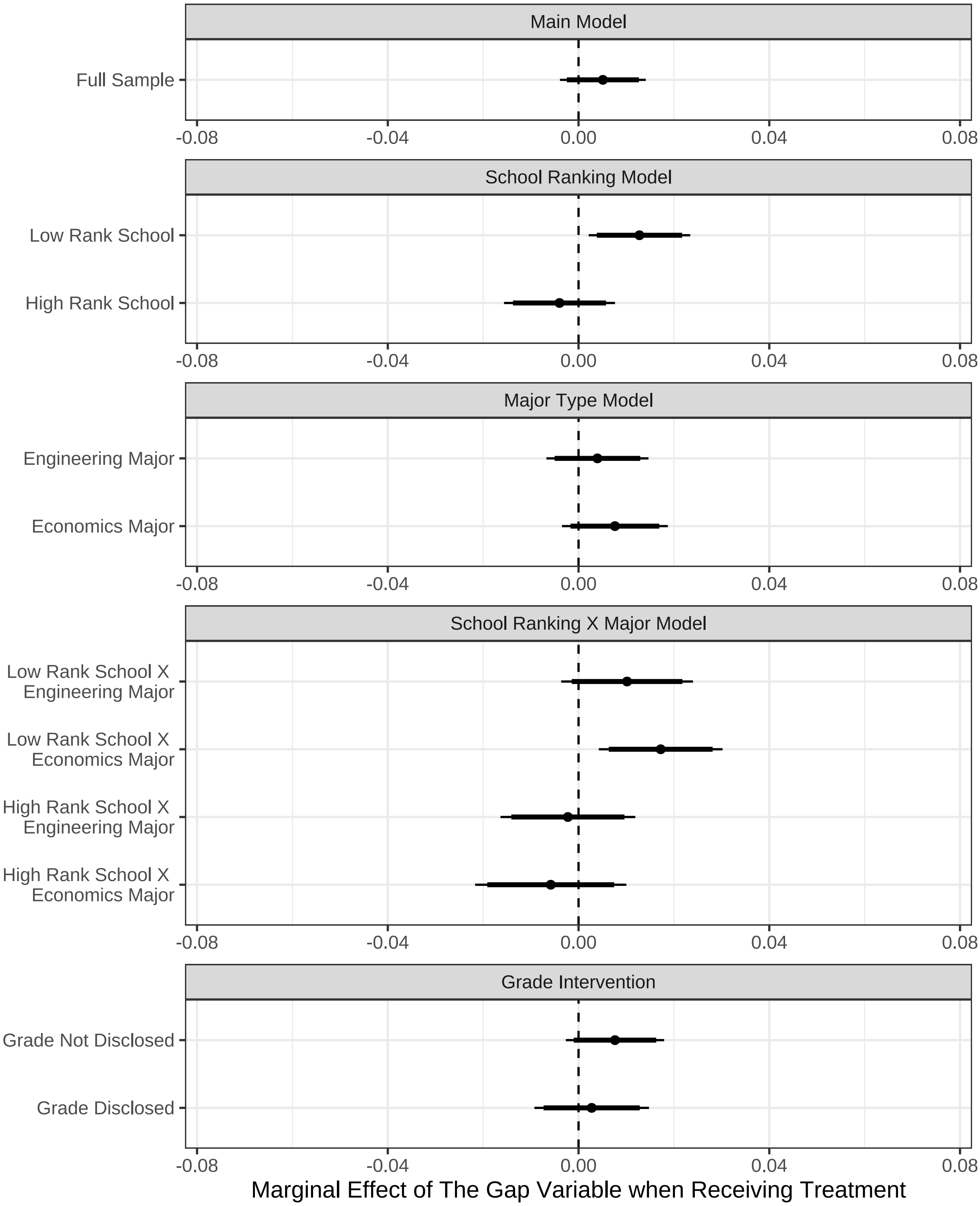

Figure D.2: Interaction coefficients of our main model using only respondents that spent more than 5 minutes answering the survey.

D.3 Attitudes Towards Entrance Exam Index

We make an index of attitudes towards entrance exams using a battery of questions where respondents were asked their agreements with statements that were either pro-exam or anti-exam. The questions all used a 5-point likert scale. Table D.2 shows the specific questions from which we constructed the index, and the mean shows the average degree of agreement to each of the seven questions (a lower value means stronger agreement). Among the seven questions, people tend to agree with the statements "Studying for entrance exams builds endurance to withstand hardship" or "The experience of exam study becomes the foundation for studying at university," suggesting that test-based students may be considered as having higher ability. Another salient reason to prefer test-based students is seen in the question "Among those who enter university through recommenda- tion, there is a large variation in academic ability," suggesting the possibility that test-optional students may have higher variance in their ability. In contrast, people also tend to agree with the statement "People who haven't done much cramming for exams tend to develop more after entering university," which may provide a reason to prefer test-optional students.

Question	Type	Mean	SD
Studying for entrance exams builds endurance to withstand hardship.	Pro-exam	2.62	1.25
The experience of exam study can sometimes hinder free thinking.	Anti-exam	3.06	1.39
The experience of exam study becomes the foundation for studying at university.	Pro-exam	2.77	1.35
Those who are good at recommendation-based entrance exams tend to have strong communication skills.	Anti-exam	3.06	1.4
Among those who enter university through recommendation, there is a large variation in academic ability.	Pro-exam	2.68	1.36
It is unfair that some people enter difficult universities without going through the rigorous entrance exam process.	Pro-exam	3.23	1.46
People who haven't done much cramming for exams tend to develop more after entering university.	Anti-exam	3.15	1.45

Table D.2: Questions that were used to construct the attitudes towards exam index. Values for the mean and standard deviation are on a 5-point likert scale with 1 indicating strong agreement and 5 strong disagreement.

To construct the index, we added the likert code for each question, with 1 indicating strong agreement and 5 indicating strong disagreement. We reverse coded the anti-exam questions, such that a 1 indicates strong disagreement and a 5 indicates strong agreement. This means that low scores indicate strong pro-exam attitudes and high scores anti-exam attitudes. We show the distribution of respondents' scores on this index in figure D.3.

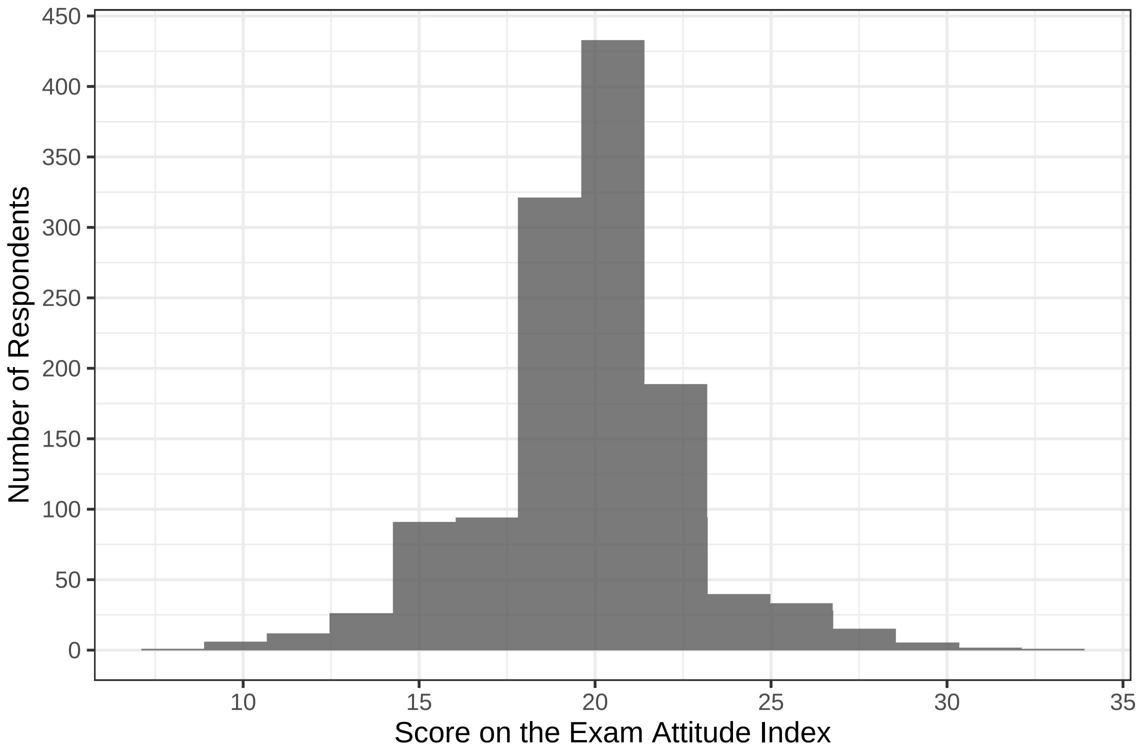

Figure D.3: Histogram of respondents' score on our additive index of attitudes towards entrance exams.

E Survey questionnaire

Survey on Human Resources and Recruitment[E.1]

We hope this message finds you well. We would like to ask for your cooperation in completing the survey mentioned in the title. This survey is targeted at professionals involved in human resources and recruitment, mainly to understand how resumes are evaluated in new graduate hiring. This survey is conducted at the request of [organization name].

Please rest assured that all information collected will be used solely for research purposes, and we will not ask for company names or personal information. All responses will be processed anonymously and numerically. We appreciate your understanding and cooperation.

1. What is your gender?
   - Male
   - Female
   - Other (Neither Male nor Female)
2. What year were you born?
   - Year: ________
3. Residential History
   - Please provide the prefecture where you currently reside. : _____ prefecture
   - Please provide the prefecture where you lived when you were 15 years old. : _____ prefecture
4. Have you been involved in recruitment at your current workplace?
   - Yes
   - No →(Exclude from survey)
5. How many employees does your company (including headquarters and branches) have?
   - 1-29 employees →(Exclude from survey)
   - 30-99 employees
   - 100-299 employees
   - 300-999 employees
   - 1000+ employees
   - Government agency →(Exclude from survey)
   - Not sure →(Exclude from survey)

[E.1] An original questionnaire in Japanese is available from the authors upon request

6. What do you think are the benefits of attending university? This question is designed to ensure that respondents are reading the entire survey carefully. If you have read this question, please select options 2, 3, and 6, regardless of your actual opinion.

    1. Better job opportunities
    2. Acquire specialized knowledge
    3. Experience youthful life
    4. Discover personal interests
    5. Build a network
    6. Change living environment
    7. Not sure

7. What do you think about the following opinions? (Select one for each statement)

	Strongly Agree	Somewhat Agree	Neutral	Somewhat Disagree	Strongly Disagree	Not sure
1. Japan is a society where academic background matters.	1	2	3	4	5	9
2. Exam studies cultivate perseverance by enduring hardships.	1	2	3	4	5	9
3. Without innate intelligence, passing an elite university entrance exam is difficult.	1	2	3	4	5	9
4. Exam studies can hinder creative thinking.	1	2	3	4	5	9
5. Exam studies serve as a foundation for university education.	1	2	3	4	5	9
6. People who succeed through recommendation-based admissions have strong communication skills.	1	2	3	4	5	9
7. There is a large variation in academic ability among students admitted through recommendation-based admissions.	1	2	3	4	5	9
8. It is unfair that some people can enter elite universities without going through tough entrance exams.	1	2	3	4	5	9
9. Students who have not gone through rote-learning exam studies develop better abilities after entering university.	1	2	3	4	5	9
10. To get into a top university through recommendation-based admissions, gaining favor with high school teachers is crucial.	1	2	3	4	5	9

8. What is the most frequently hired job category at your company?

    - Professional occupations (Doctors, nurses, lawyers, teachers, engineers, designers, etc.)
    - Management (Supervisors and executives in companies and government agencies, legislators, business owners, etc.)
    - Clerical work (General office work, accounting, internal sales, etc.)
    - Sales (Retail store owners, restaurant staff, real estate agents, insurance sales, etc.)

- Service industry (Hairdressers, chefs, waitstaff, home helpers, etc.)
- Security personnel (Police officers, firefighters, security guards, self-defense forces, etc.)
- Manufacturing & production (Product assembly, auto maintenance, food processing, etc.)
- Transport & machine operation (Truck/taxi drivers, pilots, train conductors, crane operators, etc.)
- Construction & mining (Construction workers, carpenters, electricians, etc.)
- Logistics & cleaning (Postal workers, couriers, cleaners, packers, etc.)
- Agriculture, forestry, and fisheries
- Other (Please specify: _______)

9. You will now be shown the resumes of five fictional university graduates. Please assess the likelihood of each candidate progressing to the next stage in the recruitment process for a full-time position at your company.

(A ficticious resume as in Figure 3 is shown)

- What percentage of recent students admitted to University A, Department of B, do you think were admitted through "school recommendation admissions" (which includes designated school recommendations and internal progression), rather than the general test-based admissions? ________%
- (For treatment group only) Your estimate was a%, but our calculations indicate that b% of students in recent years entered University A, Department of B through school recommendation admissions. Thus, you over/underestimated by c%. Check this box after confirming the discrepancy between your estimate and the actual percentage.
- (For all respondents) How likely is this applicant to progress to the next stage in the hiring process? (1 = Very Unlikely, 10 = Very Likely)

Very unlikely									Very likely
1	2	3	4	5	6	7	8	9	10

10. Please tell us about your current job Information.

    1. Job Position (Select closest match)
        1. No position
        2. Supervisor, Foreman, Team Leader
        3. Assistant Manager

        4. Manager
        5. Director
        6. President, Executive, Board Member
        7. Other
    2. Industry (Select closest match)
        1. Agriculture, Forestry, and Fisheries
        2. Mining, Quarrying, and Construction
        3. Manufacturing
        4. Electricity, Gas, Heat Supply, and Water
        5. Information and Communications, Mass Media
        6. Transportation and Postal Services
        7. Wholesale and Retail Trade
        8. Finance and Insurance
        9. Real Estate and Rental Services
        10. Professional and Technical Services
        11. Hospitals, Medical Care, and Welfare
        12. Schools, Education, and Learning Support
        13. Accommodation, Food Services, and Entertainment
        14. Other Service Industries
        15. Public Administration
        16. Other

11. As of April 1, 2024, how many full-time employees does your company have?
    - Total: ______ people
    - Percentage of university/graduate school graduates: _____%
    - Percentage of mid-career hires: _____%
12. What is the last (or current) school you attended?
    - Junior High School
    - High School
    - Vocational School (after high school)
    - Junior College
    - College of Technology (Kosen)
    - Four-year University
    - Six-year University (Medical, Dental, Pharmacy, etc.)

- Graduate School

13. Please answer the following questions if you have attended a junior college, university, or graduate school (including those currently enrolled or who have withdrawn).

    1. What type of institution was the last school you attended? (Select the closest match)

        - National
        - Public
        - Private
        - Other (e.g., National Defense Academy)
        - Overseas institution
        - Not sure
        - (If you selected National) What was the name of the last university or graduate school you attended? (Select the closest match)
            - Hokkaido University, Tohoku University, University of Tokyo, Nagoya University, Osaka University, Kyoto University, Kyushu University, Kobe University, Hitotsubashi University, Tokyo Institute of Technology, Tokyo Medical and Dental University
            - Chiba University, Tokyo University of Foreign Studies, University of Tsukuba, Ochanomizu University, Yokohama National University, Niigata University, Kanazawa University, Okayama University, Hiroshima University, Nagasaki University, Kumamoto University
            - Other national universities
        - (If you selected Public) What was the name of the last university or graduate school you attended? (Select the closest match)
            - Tokyo Metropolitan University, Yokohama City University, Nagoya City University, Kyoto Prefectural University, Osaka City University, Osaka Prefecture University, Kobe City University of Foreign Studies
            - Other public universities
        - (If you selected Private) What was the name of the last university or graduate school you attended? (Select the closest match)
            - Waseda University, Keio University, Sophia University, Tokyo University of Science
            - Meiji University, Aoyama Gakuin University, Rikkyo University, Chuo University, Hosei University, Gakushuin University
            - Seikei University, Seijo University, Meiji Gakuin University, Dokkyo University, Kokugakuin University, Musashi University

    - Nihon University, Toyo University, Komazawa University, Senshu University, Daito Bunka University, Asia University, Teikyo University, Kokushikan University
    - Kwansei Gakuin University, Kansai University, Doshisha University, Ritsumeikan University
    - Other private universities

  2. What was your major at the last school you attended?
     - Humanities
     - Social Sciences
     - Natural Sciences
     - Engineering
     - Agriculture
     - Medicine/Dentistry
     - Pharmacy
     - Education
     - Home Economics
     - Other (Specify: ____________________)

  3. How did you enter the university or graduate school you last attended?
     - General entrance exam
     - Public recommendation
     - AO (comprehensive) admission
     - Designated school recommendation
     - Internal progression from affiliated school
     - Other
     - No entrance exam was required

14. Regarding this survey, do any of the following apply to you? (Select all that apply. If none apply, please mark the last option.)
    - The reward was too low compared to the length of the survey.
    - I felt that the survey intended to undermine students admitted through recommendation-based admissions.
    - The similar questions continued for too long, and I got tired and answered randomly towards the end.
    - None of the above applied.

15. If you have any other comments or concerns about this survey, please write them below. (Open-ended response)

F A full list of experimental attributes

- Name [100 randomly generated names]
- Birthdate and year [the former is randomly generated while the latter is fixed to 2002]
- Gender
  - Male
  - Female
- Current university [eight private universities in the Greater Tokyo with different selectivity]
  1. Keio University (the most selective in our sample)
  2. Sophia University
  3. Chuo University
  4. Meiji University
  5. Aoyama Gakuin University
  6. Hosei University
  7. Seikei University
  8. Toyo University
  9. Teikyo University
  10. Kokushikan University
  11. Meisei University
  12. Kanto Gakuin University (the least selective in our sample)
- Current department (major) [Economics or Science]
- Academic qualifications [percentage indicates the frequency] (second treatment arm only)
  - GPA: 3.75 [16%], 3.25 [38%], 2.75[26%], 2.25[13%], 1.75[7%]
  - SPI exam score: Level 1： 2.3%, Level 2 [9.2%], Level 3 [23%], Level 4 [31%], Level 5 [23%], Level 6 [9.2%], Level 7 [2.3%]
  - A short personal statement [ten randomly generated statements based on existing resumes]
    - **Teamwork-Oriented**
      During my university years, I learned the importance of teamwork through managing a student club. By repeatedly exchanging opinions with members, we were able to make decisions that everyone agreed upon, which led to successful events. I hope to contribute as a team member at your company by applying this experience.

∗ **Problem-Solving Ability**
When faced with difficult challenges, I have the ability to calmly analyze the situation and find solutions. For example, during an internship project, we encountered a budget overrun, but I proposed a cost-cutting plan, which allowed the project to succeed.

∗ **Flexibility**
I value flexibility in the face of change. At my part-time job, I responded to sudden shift changes and always made efforts to keep operations running smoothly. I hope to use this adaptability to grow while responding to changes in your company.

∗ **Leadership**
As a seminar leader at university, I made an effort to respect the opinions of team members while facilitating progress. By encouraging active discussions and creating an inclusive environment, we achieved strong results. I hope to demonstrate leadership at your company as well.

∗ **Passion**
I always approach my goals with passion. I am especially interested in marketing and have consistently participated in related seminars and study sessions. With this passion, I hope to contribute to the growth of your company.

∗ **Communication Skills**
I am good at listening carefully to others and engaging in effective communication. In my customer service part-time job, I understood customer needs and succeeded in improving satisfaction. I hope to apply this skill at your company.

∗ **Willingness to Learn**
I have a proactive attitude toward learning new knowledge. At university, I consistently studied the latest technologies and trends and gave research presentations. I want to continue growing and become someone who can contribute to your company.

∗ **Time Management Skills**
I excel at time management and can handle tasks efficiently. While managing multiple projects simultaneously, I prioritized effectively and met all deadlines. I hope to use this skill in my work at your company.

∗ **Creative Thinking**
I am confident in generating creative ideas. In a university project, I offered proposals from a unique perspective and provided new direction for the team. I hope to contribute by introducing fresh ideas and creating value at your company.

∗ **Self-Management Ability**
I am good at self-management, always setting goals and acting systematically to achieve them. I am mindful of my own growth and strive for continuous im-

provement by accepting feedback. I want to maintain this attitude and contribute to your company.

- Extracurricular activities
  * Did not participate in club/circle activities
  * School festival planning committee
  * Education-related volunteer work
  * Welfare-related volunteer work
  * Environmental protection volunteer work
  * International exchange circle
  * Film study group
  * Advertising research group
  * A cappella circle
  * Choir circle
- Hobbies and interests
  * Reading
  * Watching baseball games
  * Watching soccer games
  * Traveling abroad
  * Dancing
  * Cycling
  * Visiting cafés
  * Karaoke
  * Yoga
  * Watching comedy shows
  * Visiting art museums
- Possession of a driving license
  * Ordinary Vehicle Class 1 Driver's License
  * None in particular