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ABSTRACT

Impact of Graduating with Honors on Entry Wages of Economics Majors*

Employers use various proxies to predict the future labor productivity levels of the job applicants. Success in school, especially in high-level coursework, is among the most widely used proxies to screen the entry-level candidates. We estimate the causal effect of graduating with honors – i.e., with a GPA of 3.00 and above out of 4.00 – on the starting wages of economics majors in Türkiye. Using comprehensive micro data on all economics majors between 2014-2018, matched with administrative records about their first jobs, we implement a regression discontinuity analysis to investigate whether there is any statistically significant jump in the starting wages at the honors-degree cutoff. We find that graduating with honors increases the wages of males, while there is no impact on females. We further document that the impact on males is almost entirely driven by the graduates of non-elite universities. In particular, graduating with an honors degree increases the entry wages of males from non-elite universities by about 4 percent, on average. We provide an explanation for these patterns using the theory of statistical discrimination. We discuss the potential reasons behind the heterogeneous signal value of graduating with honors between males versus females and elite versus non-elite university graduates.

JEL Classification: J31, J71, I26

Keywords: honors degree, economics majors, entry wages, statistical discrimination, regression discontinuity

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1 Introduction

The biggest challenge faced by the hiring firms is the difficulty of directly observing the labor productivity levels of job applicants. In other words, the classical problem of asymmetric information reduces the efficiency of firms' hiring decisions. Firms often use various proxies to screen job applicants and predict their expected productivity levels on the job. Evaluating entry-level candidates is a particularly challenging task. For four-year university graduates, the grade point average (GPA) reflects the overall performance of the student during coursework. Although success in coursework may not perfectly predict productivity in the labor market, high grades are very likely associated with high cognitive and noncognitive skills, which are reliable predictors of labor market success, and there is a feedback loop between grades, cognition, and personality traits (Hansen et al., 2004; Heckman et al., 2006; Cunha and Heckman, 2008; Cunha et al., 2010; Borghans et al., 2016). In fact, a large set of studies show that grades capture traits that are highly valued in economic and social life even more than IQ scores do.[1] Several experimental studies also show that university graduates with high GPAs are more likely to be invited for job interviews.[2] Therefore, information about the job candidates' GPA attained during university education is a valuable signal for employers.

Typically, some degrees are awarded by universities to the graduating students when the GPA passes a certain threshold, which can be fixed or variable depending on the context. In many countries, including Türkiye, students graduating with a GPA above 3.00 and 3.50 are awarded "honors" and "high honors" degrees, respectively. Most people mention those degrees on their CVs to highlight their achievements and signal their potential success/productivity in the labor market or in their further studies. Similar awards and degrees are available in many countries, albeit with different names. For example, in the British system, "merit" and "distinction" degrees are awarded to students passing certain grade thresholds. In the United States, Latin honors, i.e., cum laude, magna cum laude, and summa cum laude are used to reward students in the upper segment of the GPA distribution within the graduating class. In the absence of objective measures of labor productivity, which typically do not exist for new graduates, these degrees/awards are used by firms as valuable inputs when they screen job applicants. Graetz (2021) argues that student credentials, especially grades, have a signal value and they are used by hiring firms when information frictions are significant.

In this paper, we use detailed administrative data on all graduates from four-year economics bachelor's programs in Türkiye between 2014-2018 to estimate the causal effect of an honors degree (e.g., GPA $\geq$ 3.00) on entry-level wages of economics majors.[3] We

[1] See, e.g., Taubman and Wales (1973), Cawley et al. (1999), Bowles et al. (2001), Heckman et al. (2006), and Borghans et al. (2011).

[2] See, for example, Duckworth and Seligman (2006), Koedel and Thyurst (2012), Protsch and Solga (2015), and Piopiunik et al. (2020).

[3] "Entry wages" and "starting wages" are interchangeably used throughout the paper to describe the wage received by individuals on their first job after finishing a four-year undergraduate program.

leverage the sharp discontinuity in awarding the honors degree at the 3.00 GPA cut-off to estimate the causal effect of interest. We first use various balancing tests to show that there is no manipulation of the grades around the cut-off. Our regression discontinuity (RD) design passes all balancing/density tests. We then show that graduating with honors increases the entry wages of males, while there is no impact on females. We further document that the impact on males is almost entirely driven by the graduates of non-elite universities. In particular, graduating with an honors degree increases the entry wages of the male graduates of non-elite universities by about 4 percent, on average, and the effect size goes up to 35-39 percent for various white-collar jobs in metropolitan areas. Again, we find no impact for the female graduates of non-elite universities. These results are robust to using alternative local linear estimation procedures developed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012).

We provide an explanation for these empirical patterns using the theory of statistical discrimination. In particular, we argue that whether graduating with an honors degree is an accurate proxy for labor productivity or not is the major determinant of the impact of the honors degree on the starting wages of economics majors. We discuss the potential reasons behind the heterogeneous signal value of graduating with an honors degree between males versus females, and elite versus non-elite university graduates. First, being an elite university graduate itself may have a signal value, which likely makes the 3.00 cutoff less important when they apply for a job. Graduates of non-elite universities, on the other hand, are harder to screen as additional signals might be needed to gauge their potential labor productivity levels. Second, regardless of university prestige, we find that females have significantly higher GPAs on average than males, which implies that, conditional on unobserved ability, females get higher grades than males; hence, a high GPA is likely a less valuable signal for females' than males' potential labor productivity. Finally, consistent with our overall narrative, we show that the impact on male graduates of non-elite universities is even larger for white-collar jobs located in metropolitan areas, for which hiring decisions are likely more professionally made based on past data and observations—consistent with the statistical discrimination explanation.

Our paper is closely related to several studies investigating the labor market returns to academic performance during university education. Exploiting college policies that dismiss low-performing students on the basis of exact GPA cutoffs in an RD design, Ost et al. (2018) show that dismissal leads to a short-run increase in earnings and tuition savings, but the future fall in earnings is sufficiently large so that persisting students earn higher in the future. Bertrand et al. (2010) find, without attributing causal meanings to their estimates, that grades are among the most important determinants of subsequent labor market performance of MBAs. Walker and Zhu (2011) show using national labor force survey data that there are significant returns to degree classes for university graduates in the United Kingdom. Similar results with more details about longer-term and cross-cohort effects are reported by Naylor et al. (2016). Implementing a difference-in-differences analysis, Freier et al. (2015) document that law graduates in Germany who passed the state bar exam with an honors degree earn significantly higher wages relative to those who could not receive an honors degree. Using two full cohorts of students who graduated from a major UK university and implementing an RD design, Di Pietro (2016) finds that higher degree classifications lead to better labor market outcomes and, therefore, may have a signalling role. Feng and Graetz (2017) report using data from London School of Economics graduates that degree class causally affects labor market returns. Bleemer and Mehta (2022) exploit a rule that prevents students below a certain GPA cutoff to major in economics and estimate the causal impact of studying economics on earnings. They document significant causal return to majoring in economics. Finally, Khoo and Ost (2018) use matched administrative records from the state of Ohio and implement an RD design to estimate the impact of an honors degree on the labor market earnings of university graduates in the United States. They find that there is some signalling effect on wages, but it fades away over time. Our paper is most closely related to Khoo and Ost (2018) in the sense that (*i*) we use matched administrative records for wages (i.e., social security records) and university graduates, and (*ii*) we implement an RD analysis based on a GPA cutoff determining the honors degree award. Our analysis is different in the sense that, first, we rely on the data on the universe of all university graduates over five years, which allows us to make comparisons between elite versus non-elite universities; second, we provide a developing country perspective; and third, we focus on economics majors.[4]

The rest of the paper is organized as follows. Section 2 describes the data and institutional setting. Section 3 presents the empirical model and estimation strategy. Section 4 discusses the results. Section 5 concludes.

2 Data and institutional setting

University admissions in Türkiye are carried out based on a competitive centralized national exam, where the entrants are placed according to their exam performance and preferences. Once the students receive their scores, they list their unique major-university preferences and are placed based on their relative rankings by a computerized system. The examination is prepared and administered by the Measuring, Selection, and Placement Center (MSPC), and each year more than 2 million high school graduates take the exam. Typically, about one-quarter of the exam takers are placed in a university of their choice. The higher education system is regulated by the Council of Higher Education (COHE). All higher education institutions in Türkiye (both public and private) are subject to the

[4] Another related literature is the one investigating the impact of awards/titles on performance. Chan et al. (2014) find that both the quantity and quality of academic publications and citations of economics professors increase after receiving the John Bates Clark Medal. Neckermann et al. (2014) document that employment awards increase performance and productivity at work. Similarly, Bradler et al. (2016) find using a field experiment that public recognition improves employee performance. Ashraf et al. (2014) show that recognition and visibility improve productivity, while social comparison leads to a worsening.

regulations and strict scrutiny of COHE. The admission system in Türkiye is different than the system in the US and many other countries, such that (i) there is only one exam per year, which all students have to take on the exact same date and time, (ii) the system does not include elements of legacy admissions, students do not provide recommendation letters or rely on family networks for admissions, and (iii) the students have only one take it or leave it placement option based on their ranking in the centralized system. Hence, there is a certain degree of randomness in placements from the point view of the candidates and there is limited flexibility once the placements are announced. The students are allowed to take the exam every year, but their new scores are reduced should they enroll in a tertiary degree program in the previous year.[5]

The total number of universities in our sample period is 207. Among these, 129 are public and 78 are private (i.e., non-profit foundation). The first public university in modern Türkiye was established in 1933, followed by few others until the late 1960s. In 1971, there were in total only 9 public universities located in 4 provinces of Türkiye. Between 1971 and 2005, 69 new public and private universities were established. The remaining universities were established after 2005, when the current government undertook an education reform to increase the number of higher education granting institutions. By the end of 2019, there was at least one university in each of the 81 provinces of Türkiye.

According to the higher education statistics published by COHE[6], the number of male and female students who graduated from a four-year undergraduate degree program in the 2017/2018 academic year were 215.6 thousand and 239.4 thousand, respectively. Among those graduates, 120.5 thousand male and 159.6 thousand female students completed a formal bachelor's degree, while the rest graduated from distance learning or open education programs. Those statistics also show that, in the 2017/2018 academic year, 9.7 thousand males and 10.8 thousand females graduated from the economics programs. Although more females obtained a degree in economics than males in 2018, there is a large gender discrepancy in enrollment to economics programs in general. For example, the COHE statistics suggest that, in the 2018/2019 academic year, 19 thousand students enrolled in an undergraduate program in economics, but only 7.4 thousand of them were female. This is in line with the gender imbalances in economics programs that are observed in other countries such as in the US (Bayer and Rouse, 2016; Bayer and Wilcox, 2019).

One of the most common job finding routes for the youth in Türkiye is application through private employment agencies that post online vacancies. The 2018 Household Labor Force Surveys show that in 2018, about 49.9 percent of college graduates aged between 22 to 25 applied to jobs using those online platforms. The same figure is about 47.2 percent for 20 to 29-year-old graduates.[7] These platforms typically ask about the

[5]Note that these rules can be fine-tuned or changed over time; therefore, the description and statistics provided in this section would reflect the setting at the time this paper was written.

[6]For more details, see https://istatistik.yok.gov.tr/.

[7]These figures are for graduates of social and management sciences. Unfortunately, the Household Labor

GPA information of the applicants and, hence, the academic performance of the applicants is observed by the employers. Alternatively, the applicants can directly provide this information on their CVs; or this information might be revealed during the interviews or at the time the applicant presents proof of graduation.

We focus on economics majors for several reasons. Economics is a social science with a wide range of employment opportunities. Unlike the STEM degrees, an economics degree at the undergraduate level in Türkiye does not have a strong signal value in terms of the technical and analytic capacity of individuals, whereas engineering or medicine undergraduate degrees are traditionally much more difficult to get in and considered to offer more challenging curricula. The same is true for undergraduate-level law degrees. Hence, those fields themselves have a high signal value for ability. This is also observable in the starting wages of recent graduates, which show how labor markets value certain fields/disciplines relative to others. According to the administrative records, only 4 percent of the economics graduates land jobs that pay above 10,000 TL per month upon graduation, which is approximately 625 USD[8], whereas the corresponding figure is 52 percent for medicine, 24 percent for computer engineering, and 20 percent for law. The median starting wage for college graduates is approximately 350 USD.[9] The STEM, medicine, and law programs are also specialized fields such that the diploma itself is a license for certain occupations, which cannot be filled with any other undergraduate degree. On the other hand, entry-level jobs that can be filled by economists in Türkiye—such as banking, sales, accounting, and customer relations—are typically those which can also be filled by most four-year tertiary education degrees, including the STEM—should the individuals prefer. An obvious question is whether management or business degrees at the undergraduate level are any different. Business programs are also traditionally considered to be prestigious in Türkiye and usually have high placement rankings conditional on the degree-granting university. Thus, business programs can be said to have a stronger signal value in comparison to economics programs in the Turkish context.

Our first data source is the micro-level administrative data on university graduates. We use the universe of graduates who obtained a bachelor's degree in economics between 2014 and 2018, but exclude graduates of the distance learning, open education, and evening education programs.[10] This data set includes information on the enrolled program, faculty, date of enrollment, date of graduation, and graduation GPA. By the regulations of COHE, grading in the Turkish higher education system follows the American system, and the GPA is measured out of 4.00. Table 1 summarizes the list of universities that grant economics degrees and the corresponding graduate shares in our data set.

Force Surveys only include information on 22 broad ISCEDF13 categories and not on the specific field of study.

[8]The average annual exchange rate for 2022 is taken as 16 TL per USD.

[9]Source: Household Labor Force Surveys and the UniVeri Project; https://www.cbiko.gov.tr/en/projects/uni-veri.

[10]The names of bachelor's programs in Türkiye are not completely harmonized. We check the curriculum of each economics degree program granting institution and ensure that our data set includes graduates from those programs with a standard economics curriculum.

We classify universities as elite and non-elite universities. The elite universities are Koc University, Bilkent University, Sabanci University, Bogazici University, and Middle East Technical University (Orta Dogu Teknik Universitesi). Traditionally, two older public universities, Bogazici University, and Middle East Technical University have been considered the top public universities in Türkiye and they follow the American curricula. In addition to those two, three relatively younger private universities, Bilkent University, Koc University, and Sabanci University also closely follow the American curricula and are able to attract the highest-ranked students with generous full scholarships. In particular, the cutoff rankings for placement in the economics programs in those universities with a full scholarship were between 0.008-0.362 percentiles in 2018.[11] The reason why we make the elite versus non-elite university distinction is to separate out the signal value of attending a prestigious university from the signal value of completing an economics program with an honors degree, as the former is perceived to be highly correlated with the ability, irrespective of the graduating GPA.

We match the graduate data with the micro-level administrative data on employment provided by the Social Security Institution (SSI) under the Ministry of Labor and Social Security.[12] Employment data include information on monthly net wages, location, sector codes (NACE Rev 2.), occupation codes (ISCO-88), province of employment, year of labor market entry, and whether the individual is employed in the public or private sector. We focus on the starting wage upon first employment registration at the social security system for each graduate. We use real wages at 2014 prices. We do not count the internships or part-time employment during university education as first employment, however employment up to 6 months prior to graduation is included in the analysis if the individual does not quit before graduation. We also exclude any individuals who enroll in a graduate program, because our main purpose is to understand the wage outcomes of the undergraduate degree holders upon graduation. More specifically, we observe whether an individual is enrolled in a graduate program in Türkiye, however, the data do not allow us to see whether the individuals go abroad for graduate degrees. Yet, we do not believe that brain drain is a particular concern for identification in our analysis because students that have GPA above 3.50 are more likely to find scholarships abroad and less likely to move back after graduation, and those students do not fall into our optimal bandwidth estimates.

Our final data consist of 44,950 observations on economics majors, 1,675 graduates from elite schools, and 43,275 from non-elite schools. Summary statistics in Table 2 show that females on average graduate with a higher GPA compared to males for both elite and non-elite universities. The share of students graduating with an honors degree is significantly higher in elite universities compared to non-elite universities. There are also

[11] Bilkent University, Koc University, and Sabanci University have 4 types of admission; full scholarship, 50 percent scholarship, 25 percent scholarship, and no scholarship. The cutoff rankings for placement with no scholarship were between 13.8-26 percentiles for those three universities.

[12] The final data set is fully anonymized.

significant differences in mean wages across graduates of elite and non-elite universities. Interestingly, unconditional mean wages are highest for female graduates of elite universities, being even higher than their male classmates. And not surprisingly, mean wages are lowest for females graduating from non-elite universities. Distributions of the year of graduation and year of labor market entry look fairly similar for our sample of elite graduates as employment rates are significantly higher for this group. On the other hand, there are discrepancies between the year of graduation and the year of labor market entry for non-elite university graduates. There may be two reasons for that. First, demand is lower and unemployment duration is longer for these graduates, more so if they reside in non-metropolitan provinces. And second, the composition has been changing. Between 2010 and 2018, 70 new public and private universities were established, while 17 universities were closed and the students were transferred to other universities after the 2016 coup attempt.

3 Empirical strategy

In this section, we describe our empirical approach and econometric strategy. Our baseline analysis relies on a local linear RD procedure, where the bandwidth is optimally calculated within the model. Let $d_i = d(r_i) = \mathbb{1}(r_i \geq \bar{r})$, where the running variable r_i is the graduating GPA for individual i and $\bar{r}$ is the cutoff value (GPA=3.00). In other words, $d_i = 1$ if $r_i \geq 3.00$ and $d_i = 0$ if $r_i < 3.00$, which is the discrete rule governing the honors degree-awarding.

The standard potential outcome framework suggests that the entry wage, w_i, which is our outcome variable, takes the value $w_{1,i}$ if $d_i = 1$, and $w_{0,i}$ if $d_i = 0$. The impact of honors degree on entry wages for individual i can, therefore, be expressed by $w_{1,i} - w_{0,i}$. But the well-known problem here is that an economics major can either graduate with a GPA above or below 3.00. In other words, the researcher cannot observe both $w_{0,i}$ and $w_{1,i}$ for the same individual (Imbens and Lemieux, 2008; Angrist and Pischke, 2009). Our RD analysis allows us to compare the average outcomes of individuals who are just below and above the GPA cutoff as if the honors degree is randomly assigned.[13]

Under smoothness and continuity assumptions around the GPA cutoff, the treatment effect can be identified by a simple comparison of the right and left limits of the conditional expectation function as follows (Hahn et al., 2001):

$$\lim_{r_i \searrow \bar{r}} \mathbb{E}[w_i|r_i] - \lim_{r_i \nearrow \bar{r}} \mathbb{E}[w_i|r_i] = \mathbb{E}[w_{1,i} - w_{0,i}|r_i = \bar{r}] = \mathbb{E}[\theta_i|r_i = \bar{r}], \tag{1}$$

where θ_i is our parameter of interest. Following Gelman and Imbens (2019), we assume a linear relationship between the outcome and running variables, where we also allow for

[13]Unlike the setting in Khoo and Ost (2018), there are no variable cutoffs in our context—e.g., the degree cutoffs are not different across schools and do not vary over time.

differential trends around the cutoff. The final model we estimate becomes:

$$w_i = \alpha + \theta d_i + \beta_1(r_i - \bar{r}) + \beta_2 d_i \cdot (r_i - \bar{r}) + \epsilon_i, \qquad (2)$$

where β_1 and β_2 characterize the differential trends around the cutoff, and ϵ_i is an error term.

One of the key issues in continuity-based RD analysis is bandwidth selection. We implement the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012).[14] To improve the precision of our estimates, we include year-of-birth, year-of-graduation, and university-fixed effects in all of our regressions. We also control for university-academic year interaction terms to account for university-specific trends in entry wages. Note that, since we use multiple graduating cohorts in our analysis, the wage variable needs to be comparable across years of graduation. Accordingly, wages are deflated by the Consumer Price Index (CPI) and included in the regressions in 2014 prices.

3.1 Validity of the RD design

This subsection presents the basic RD diagnostics. In any RD analysis, the validity of the design critically relies on the assumption that agents cannot manipulate their treatment status. However, if round numbers have a signal value, then agents might have incentives to exert more effort to pass certain thresholds. Pope and Simonsohn (2011) explore three cases to show this point. In the context of professional baseball, Pope and Simonsohn (2011) find that players modify their behavior as the season is about to end, seeking to finish with a batting average just above rather than below 0.300. Similarly, the study shows that high school students are more likely to retake the SAT after obtaining a score just below rather than above a round number. The third setting is an experiment employing hypothetical scenarios where participants report a greater desire to exert more effort when their performance was just short of rather than just above a round number. We argue that, while in our case, students close to the honors degree cutoff might exert more effort, it is not possible for any student to perfectly manipulate grading, as the graduating GPA is earned over the years and depend on a lot of factors outside their control, such as the relative performance of other students.[15] Indeed, Lee and Lemieux

[14]The Imbens and Kalyanaraman (2012) (IK) procedure chooses the bandwidth by minimizing the mean-squared error (MSE) of the local linear regression estimator. The Calonico et al. (2017) (CCT) procedure also minimizes the MSE; but, additionally, it implements a bias correction and produces heteroskedasticity-robust standard errors using a second-order plug-in rule. Calonico et al. (2014) indicate that the IK procedure likely yields a large bandwidth and the bias-correction algorithm introduced by the CCT procedure fine-tunes the IK bandwidths. Moreover, the IK bandwidths may be more sensitive to outliers and do not account for non-normal errors. Consistent with this view, the IK bandwidths reported in our paper are larger than the CCT bandwidths. Reassuringly, the qualitative and quantitative nature of our estimates does not exhibit notable differences between the two procedures. Given the more robust nature of the CCT procedure, our preferred specification is the one reporting the CCT bandwidths. Note that the results still hold when we use a local randomization approach, which aims to address potential approximation errors when the running variable is discrete (Cattaneo et al., 2023).

[15]In a similar study, Ost et al. (2018) rely on an RD design which exploits the college policies in Ohio that dismiss low-performing students on the basis of 2.0-cutoff to estimate the returns to college enrollment and

(2010) argue that as long as individuals—even while having some influence—are unable to precisely manipulate sorting into the treatment status, the variation in treatment near the threshold is as if randomly assigned.

To verify the assumption that there is no manipulation of the grades around the threshold, we first examine whether the density of the forcing variable (the GPA) is continuous at the cutoff. McCrary (2008) shows that if there is no perfect manipulation, then the forcing variable in an RD design should be reasonably continuous. Indeed, Figure 1 demonstrates that there is no abnormal spike at the 3.00 cutoff in our data. Next, we plot the McCrary density distributions. Figure 2 shows that there are no discrete jumps for males or females at the 3.00 cutoff. In Table 3, we report the p-values and the number of observations for our McCrary density plots. In line with the figures, p-values of the test for the null hypothesis that there is no discrete jump at the cutoff are sufficiently high for all groups, except for male graduates of elite universities. While the p-value of 0.106 for this group is only marginally insignificant, we argue that it does not pose a threat to our identification as there is no evidence of discontinuity for any other groups and as our main focus is on male graduates of non-elite universities.[16]

Another important requirement for a valid identification in an RD design is to test the covariate balance between control and treatment groups around the 3.00 cutoff. In Figure 3, we plot the year of birth, year of labor market entry, age, and year of graduation, and inspect their balance around the cutoff. The figures are reassuring as there are no significant jumps for any of the covariates at the cutoff, meaning that there is no visual evidence of manipulation based on these observables. In Table 4, we also report the p-values of covariate balance tests for our observables using the optimal bandwidths proposed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012). As the table clearly shows, there is no statistically significant difference in observable characteristics between our control and treatment groups around the cutoff.

4 Results and discussion

4.1 Visual evidence

We first present some visual evidence comparing the earnings outcomes for university graduates just below and above the honors degree cutoff. Specifically, Figures 4, 5, and 6 broadly display visual evidence for the entire sample, elite universities, and non-elite universities, respectively. Each figure also provides a gender-specific visualization. For almost all the figures, there is a fanning out in wage observations. While there is no visible discontinuity for the pooled sample with both genders in Figure 4, there is a slight discrete jump for males in the whole sample in Figure 5 and for non-elite schools in Figure 6. This

earnings. The study provides several checks and arguments that manipulation of the running variable around the 2.0-cutoff does not drive the results of the paper.

[16] The donut hole estimates we present in Appendix B also confirm that the results are not sensitive to the observations around the cutoff.

preliminary evidence suggests that, if there is any statistically significant discontinuity at the cutoff, it should be mainly driven by male graduates of non-elite universities.

In Figure 7, we further zoom in and more explicitly present the discontinuity in the earnings of male graduates of non-elite universities using a narrower window within the -0.216 and $+0.216$ neighborhood of the 3.00 cutoff, which is the optimal bandwidth provided by the Calonico et al. (2014, 2017) procedure. In this figure, the discontinuity around the cutoff is highly visible. Below, we complement the visual evidence with the RD analysis results supported by several alternative specifications and robustness checks.

4.2 Regression results

We present our core results in Tables 5, 6, and 7. In these estimations, we use the optimal bandwidth algorithms proposed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012), and we further check the robustness of our results by using alternative kernel functions. Moreover, we use manual bandwidths to examine the robustness of our results to changes in the bandwidth.

We first examine how crossing the 3.00 GPA threshold affects starting wages using the data on all economics majors in Table 5. The first panel includes pooled data for males and females, whereas the second and third panels provide results for males and females, separately. In the first panel, we do not find a statistically significant effect of passing the cutoff on the starting wages. However, in the second panel, there is a statistically significant increase in the starting wages for the male sample, with an effect size between 3 to 5 percent. Optimal bandwidths are between 0.219 and 0.257 for the Calonico et al. (2014, 2017) algorithm, whereas they are almost twice as large for the Imbens and Kalyanaraman (2012) algorithm. There is no statistically significant effect for the female sample.

Next, we explore whether or not the results are affected by university prestige. Our sample is divided into two categories, elite versus non-elite universities, as explained in Section 2. We run the same specifications as above; but, this time separately for elite and non-elite universities for both gender categories. For the elite universities, estimation results in Table 6 show that graduating with an honors degree has no effect on entry wages for males and females. The optimal bandwidths are comparable in size to the bandwidths in the pooled sample, but all coefficients are insignificant with large standard errors—perhaps due to the smaller sample size. On the other hand, results in Table 7 for non-elite university graduates reveal a different picture. We find a positive and statistically significant effect of graduating with honors on the entry wages of male students of non-elite universities. The coefficient size is between 2.9 and 4.3 percent for this group of graduates—with similar optimal bandwidth sizes as before. These findings suggest that the increase in entry wages that we find for males in Table 5 is mainly driven by the graduates of non-elite universities.[17] As before, we find no such effect for female graduates

[17] Note that our sample consists of employed individuals only. If the probability of employment is systematically

of non-elite universities.

To check the robustness of our results, we first explore the effects using manual bandwidths.[18] In particular, we estimate the coefficients of manual RD regressions, where the log real wage is the dependent variable. Our variable of interest is the dummy on the GPA cutoff which indicates whether the graduating GPA is higher than 3.00 or not. The specification includes the distance to the cutoff and the interaction between the distance and the cutoff dummy. Rather than imposing a few bandwidths, we provide a large range of estimations, starting from the most conservative symmetric bandwidth of $[2.99, 3.01]$, increasing the width by 0.01 points up until the $[2.75, 3.25]$ bandwidth for each group. We then repeat the same procedure, but this time we start with the asymmetric bandwidth $[2.97, 3.01]$ and increase the upper bound of the bandwidth by 0.01 points up until $[2.97, 3.25]$. The selection of the lower bound of 2.97 GPA is somewhat arbitrary, but in Appendix A, we repeat the same procedure using a minimum lower bound of 2.95 and show the results are highly robust.

We provide our estimation results as coefficient plots with 90 percent confidence intervals in Figures 8-11. In panel (a), we display the estimates for symmetric bandwidths and, in panel (b), we show the results for asymmetric bandwidths in all figures. Figure 8 shows the estimations for male graduates of non-elite universities. The estimations point out to an increase in real wages for all bandwidths. Although the coefficients are slightly less precise for narrower bandwidths—due to the small sample size—the coefficient size is quite stable, especially for bandwidths $[2.96, 3.04]$, $[2.95, 3.05]$, and $[2.94, 3.06]$. Estimations in panel (b) also confirm that the coefficient sizes and confidence intervals are almost identical as we fix the lower GPA bound at 2.97 for almost all bandwidth selections. Furthermore, all coefficient estimates after the bandwidth $[2.97, 3.04]$ are statistically significant either at 1 or 5 percent significance levels and none of the confidence intervals includes zero. These estimations imply that, for male graduates of non-elite universities with GPAs falling into these bandwidths, having an honors degree is associated with an increase of around 11 percent in starting wages in comparison to barely missing the cutoff.

We next repeat the same exercise for female graduates of non-elite universities. Figure 9 shows that the coefficient estimates are imprecise for some of the tight bandwidths around the 3.00 cutoff, but all point out to an effect size of zero. The coefficient estimates are negative but they are not distinguishable from zero for asymmetric bandwidths with a minimum 2.97 GPA. We see a similar pattern for graduates of elite universities, both for males and females in Figures 10 and 11. The coefficient estimates are imprecise for the most conservative bandwidths; but, overall, they point out to a zero effect of honors degree on starting wages. The null effects are visibly stronger if we restrict the lower

higher on the right of the cutoff than on the left (as we discuss in Section 2), then the magnitude of these estimates might be biased downward.

[18] See, for instance, Ost et al. (2018), who rely on a fixed bandwidth of 0.5-grade points in a study estimating the effect of dismissal policies for low-performing students on their future earnings on the basis of exact GPA cutoffs.

bound of the bandwidth at 2.97 for male graduates of elite schools. We conclude that the robustness checks based on the manual RD estimations confirm the earlier findings that the honors degree increases the starting wages of males who graduated from non-elite universities but not the wages of other graduates. However, we acknowledge that the lack of statistical power due to the small sample size for elite students is a limitation of the manual bandwidth estimates, and, hence, the results for the elite universities should be interpreted with caution.

4.3 Discussion of the baseline results and potential mechanisms

Our results show that graduating with an honors degree increases the entry wages of economics majors, especially for male graduates of non-elite universities. It is an interesting phenomenon that we consistently find a positive and statistically significant effect for males but not for females of non-elite universities, or for elite university graduates. In what follows below, we try to explain and reconcile our findings with statistical discrimination theories.

If the GPA is a proxy for ability, then one would expect a continuous increase in the starting wages of university graduates as the GPA goes up, which we roughly observe in our baseline RD plots. In this paper, we test whether there is a statistically significant jump in the starting wages at the honors degree cutoff. The existence of such a jump might have three meanings. The first possibility is that, at the cutoff margin, a student graduating with a GPA of 3.00 has an additional skill valued by the hiring firms in comparison to a student graduating with a GPA of 2.99. This is not true, because the graduating GPA is just a weighted average of grades obtained from different courses throughout undergraduate education. Therefore, it is a measure of success in coursework and there is no additional skill attached to a higher GPA. The second possibility is that there is an imbalance in our sample around the cutoff that could generate such a jump. We clearly establish in Section 3.1 that our sample is well-balanced around the 3.00 cutoff. The final possibility is that the honors degree is attributed an additional signal value by the hiring firms. The theory of statistical discrimination suggests that, when hiring firms experience difficulties in assessing the potential productivity of job applicants, they use various signals that convey useful information about the candidates. Typically, these signals are learned by the firms based on the data they collected over time.

The most likely explanation is that firms learn over time that, on average, females tend to have higher GPAs than males, which we show in our descriptive statistics in Table 2; therefore, they might not think that an honors degree carries a useful signal value about the labor productivity of female applicants. Males, on the other hand, are assessed in two groups. (1) Male graduates of elite universities are not screened according to a GPA-cutoff rule—as it is highly likely that graduating from an elite university is itself a signal. (2) Male graduates of non-elite universities constitute a substantially mixed group subject to large uncertainties about their potential labor productivity levels and, accordingly, the hiring firms use the honors degree threshold to screen them.

The theory of statistical discrimination suggests that, when ability and individual characteristics are not perfectly observed, employers use several proxies to screen the applicants (Weiss, 1995). The signalling model of Spence (1974) shows that individuals invest in education because it sends information to employers about their productivity. In that respect, the finding of null effects for elite university graduates may not be surprising. After all, each year around two million 12^{th} graders in Türkiye take the national university placement exam and only the top scorers in the 0.008-0.362 percentiles are placed at elite universities. Therefore, being an elite university graduate itself gives a strong signal of ability and/or industrious personality traits.

For non-elite university graduates, on the other hand, it is important to understand why degree classifications of male graduates are treated differently than classifications of females by employers. Based on a meta-analysis of 369 studies involving the academic grades of over one million boys and girls from 30 different nations, Voyer and Voyer (2014) show that girls are ahead in every subject and tend to get better grades than boys. On the other hand, while girls earn higher grades than boys, they do not outperform boys on achievement or IQ tests. Duckworth and Seligman (2006) show that this difference stems from the fact that girls tend to be more self-disciplined and conscientious, which is more relevant to grades than to achievement tests.

Theories of statistical discrimination can help reconcile our findings. In the basic model of statistical discrimination, uncertainty about worker productivity or stability may lead to discrimination by employers against race or gender groups based on real or perceived average differences (Phelps, 1972; Aigner and Cain, 1977; Blau and Kahn, 2017). For this model to generate discrimination, it suffices to have equal average productivity but different variances across different groups. In Phelps (1972), employers do not observe productivity, but they use the test scores as an unbiased predictor for productivity. Assuming that black and white workers have the same average productivity but the variance for black workers is higher, then at low test scores, a white worker is predicted to excel over a black worker with the same test score. The reason is that although the test scores are the same for both groups, the expected productivity of the black worker is lower than the expected productivity of a white worker. On the other hand, this model predicts that high-scoring whites will be paid less than high-scoring blacks as the expected productivity for blacks will be higher than whites (Aigner and Cain, 1977). In the signalling model of Spence (1974), discrimination also arises when the cost of achieving a high test score is negatively correlated with ability. In this model, groups might have identical productivity distributions but face different signalling costs; or, face the same signalling costs but the employers' perceived threshold for the signal value of ability can be different across groups.

These models are well-suited to explain our results. Since girls are known to excel over boys over self-discipline and conscientiousness, the productivity variance for girls could be perceived as smaller. Blau and Kahn (2017) argue that over the last decades, women's increasing levels of schooling, commitment to the labor market, and higher representation in better jobs might have led to a reduction in employer incentives for statistical discrimination. Hence, an honors degree may have less signalling value for female graduates of non-elite universities. Türkiye is a country with low levels of female labor force participation rates, hence being on the job market might be a sufficiently strong signal for productivity and labor market commitment. On the other hand, if achieving an honors degree is perceived to be on average more costly for males for various reasons, then an honors degree might have a stronger signal value for expected productivity for male graduates of non-elite universities. Hence, employers might be willing to pay higher wages for males of non-elite universities, based on the observed degree classification.

Finally, the grading standards for economics majors may be different across universities. The university fixed effects and university-year interaction terms roughly capture how those differences affect wages. In a different set of regressions, we standardized the GPAs around mean zero and unit standard deviation at the university level and repeated our RD analysis; but, the qualitative and quantitative nature of our results did not change. Any remaining inter-university variation in grading standards may add to the uncertainty in the signal value of the GPA when the firms evaluate the candidates, which strengthens our statistical discrimination argument.

4.4 Additional analyses and sensitivity checks

Donut RD approach. As a robustness check, we use a donut RD approach to test whether our estimates are sensitive to the observations at the cutoff (Barreca et al., 2011, 2016). The results in Table A3 of Appendix B show that our findings are robust to dropping observations at the threshold—see Appendix B for a more detailed discussion of these results.

Results for the "good" jobs. To support the statistical discrimination mechanism that we propose, we test whether our results are driven by the "good" jobs, which are very likely offered by larger firms located in urban metropolitan areas. Those firms generally have better human resources practices relative to the firms located in the less developed regions in Türkiye. One can imagine that larger firms (located in metropolitan areas) with better hiring processes are the firms that are more likely to use their past data and observations to develop a screening strategy—consistent with the idea of statistical discrimination. Using the ISCO-08 codes that are available in our administrative data set and employing the procedures described by ILO (2018) and ISCED (2012), we classify "good" jobs based on the education requirements of the job. We also restrict our sample to the metropolitan areas in Türkiye. We find that when we restrict our sample to good jobs that are available in metropolitan areas (which are mostly white-collar jobs that require professional and managerial skills), graduating with an honors degree leads to a large increase in the starting wages for male graduates of non-elite universities, but not for female graduates or for students graduating from top universities. These results suggestively support our main hypothesis that statistical discrimination is exercised by firms to screen job applicants with uncertain labor productivity levels. Please see Appendix C for the rest of the details on our data construction, analysis, results, and interpretation of the findings.

Results for the STEM graduates. Next, we extend our analysis to the graduates of undergraduate programs other than economics. However, before we present the results, it is important to acknowledge the constraints with respect to the context and data availability for other undergraduate programs. The subject names and curriculum structures of many non-economics programs vary substantially across the universities in Türkiye.[19] On top of this excessive heterogeneity in subject names, many universities specialize in certain subject areas—e.g., not all universities offer degrees in every discipline. Moreover, subject names in a given university may change over time. These restrictions significantly limit our ability to cover all fields of study consistently in our data horizon. That said, there are certain disciplines that can be consistently observed over the data horizon in a majority of universities with the same (or very similar) subject names. These are (*i*) economics, (*ii*) law, (*iii*) medicine, and (*iv*) many fields in STEM. For the law and medicine majors, the graduates follow certain career paths that remove variation in starting wages.[20] Therefore, the starting wages of law and medicine graduates in Türkiye are determined by factors unrelated to the standard market-based job application, screening, and competitive wage determination processes. This leaves us with economics and STEM majors. In Table A1, we present the results for the STEM majors by repeating our RD analysis using the data for STEM graduates. We find that there is no statistically significant jump in the starting wages of STEM graduates at the honors degree cutoff. This is consistent with the explanation provided earlier in the paper—see Section 2, where we say that being a STEM graduate is itself a signal and, therefore, there may be no additional wage premium at the 3.00 GPA cutoff.

Results by university establishment dates. To support our statistical discrimination explanation, we present a set of RD estimates by university establishment dates. 2006 is a key year for university openings in Türkiye. The total number of new universities established since 2006 is 131. Between 1933-2005, 77 universities were established in total. Table A2 presents the estimates for male and female graduates of non-elite universities by

[19]For example, the alternative subject names for undergraduate programs in business schools include Finance, Finance & Accounting, Banking & Finance, Management, Management & Tourism, Management & Accounting, Management Informatics, Business & Information Management, and etc. Those differences are also observed for a wide variety of subjects in social sciences, public policy/administration, architecture, arts, and education.

[20]The graduates of medicine programs take the centralized "Examination for Specialty in Medicine," and, if they succeed in the exam, they get another 4 years of training in their field of specialization during which they get paid a fixed salary determined by the government. If they do not succeed, they start working as a "medical practitioner" and they again get paid a fixed salary determined by the government. The graduates of the law programs also follow certain pre-determined career paths that remove variation in starting wages. If they want to become a judge or prosecutor, they need to take a centralized exam and, if they succeed, they start with a fixed salary determined by the government. If they choose to become a lawyer, there is a mandatory long-term internship program during which they work in a law firm and receive a pre-determined salary.

dividing the sample into two—for universities established before and after 2006. We find that our baseline results for the male graduates of the non-elite universities are mostly driven by the older universities. The explanation is as follows. Being a male graduate of a non-elite university is subject to lots of uncertainty in terms of labor productivity and hiring firms use the 3.00 GPA cutoff as a proxy to screen the graduates in this group. However, the 3.00 GPA cutoff is a more reliable signal for the older universities as the hiring firms have learned about the signal value of the honors degree over time, while it is a less reliable signal for the new universities. This is consistent with the statistical discrimination explanation we provide.

5 Concluding remarks

Employers use various proxies to gauge the expected productivity of job applicants. Success in school, especially in high-level coursework, is among the most widely-used proxies to screen candidates. We estimate the causal effect of graduating with honors—i.e., with a cumulative GPA of 3.00 and above—on the starting wages of economics majors in Türkiye. Using comprehensive micro data on all economics majors between 2014-2018, matched with administrative records about their first jobs, we implement a regression discontinuity analysis to investigate whether there is any statistically significant jump in starting wages around the cumulative GPA cutoff. We find that graduating with honors increases the wages of males, while there is no impact on females. We further document that the impact on males is almost entirely coming from those who graduated from non-elite universities. In particular, graduating with an honors degree increases the entry wages of males from non-elite universities by about 4 percent, on average. We provide an explanation for these patterns using the theory of statistical discrimination. We argue that whether graduating with honors is an accurate proxy for labor productivity or not is the major determinant of the impact of honors on starting wages of economics majors.

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Table 1: Universities in our sample and their sample shares

University name	Share	University name	Share
Adiyaman Universitesi	0.0070	Istanbul Medeniyet Universitesi	0.0006
Afyon Kocatepe Universitesi	0.0115	Istanbul Teknik Universitesi	0.0016
Agri Ibrahim Cecen Universitesi	0.0011	Istanbul Ticaret Universitesi	0.0023
Akdeniz Universitesi	0.0109	Istanbul Universitesi	0.0550
Aksaray Universitesi	0.0027	Izmir Ekonomi Universitesi	0.0026
Altinbas Universitesi	0.0004	Izmir Katip Celebi Universitesi	0.0006
Anadolu Universitesi	0.0264	Kadir Has Universitesi	0.0015
Ankara Yildirim Beyazit Universitesi	0.0011	Kafkas Universitesi	0.0088
Ankara Universitesi	0.0048	K.Maras Sutcu Imam Universitesi	0.0124
Antalya Bilim Universitesi	0.0002	Karabuk Universitesi	0.0050
Ardahan Universitesi	0.0046	Karadeniz Teknik Universitesi	0.0208
Artvin Coruh Universitesi	0.0007	Karamanoglu Mehmetbey Universitesi	0.0169
Ataturk Universitesi	0.0177	Kastamonu Universitesi	0.0046
Atilim Universitesi	0.0012	Kilis 7 Aralik Universitesi	0.0075
Avrasya Universitesi	0.0006	Kirikkale Universitesi	0.0102
Aydin Adnan Menderes Universitesi	0.0206	Kirklareli Universitesi	0.0083
Bahcesehir Universitesi	0.0037	Kirsehir Ahi Evran Universitesi	0.0068
Balikesir Universitesi	0.0238	**Koc Universitesi**	0.0085
Bandirma Onyedi Eylul Universitesi	0.0005	Kocaeli Universitesi	0.0173
Bartin Universitesi	0.0081	Kutahya Dumlupinar Universitesi	0.0275
Baskent Universitesi	0.0021	Maltepe Universitesi	0.0012
Bayburt Universitesi	0.0119	Manisa Celal Bayar Universitesi	0.0267
Beykent Universitesi	0.0075	MEF Universitesi	0.0001
Bilecik Seyh Edebali Universitesi	0.0177	Mersin Universitesi	0.0071
Bitlis Eren Universitesi	0.0008	Mugla Sitki Kocman Universitesi	0.0173
Bogazici Universitesi	0.0101	Munzur Universitesi	0.0052
Bolu Abant Izzet Baysal Universitesi	0.0136	Mus Alparslan Universitesi	0.0029
Burdur Mehmet Akif Ersoy Universitesi	0.0017	Necmettin Erbakan Universitesi	0.0022
Canakkale Onsekiz Mart Universitesi	0.0140	Nevsehir Haci Bektas Veli Universitesi	0.0073
Cankaya Universitesi	0.0018	Nigde Omer Halisdemir Universitesi	0.0131
Cankiri Karatekin Universitesi	0.0077	Nisantasi Universitesi	0.0003
Cukurova Universitesi	0.0170	Ondokuz Mayis Universitesi	0.0042
Dogus Universitesi	0.0033	Ordu Universitesi	0.0123
Dokuz Eylul Universitesi	0.0349	**Orta Dogu Teknik Universitesi**	0.0074
Ege Universitesi	0.0130	Osmaniye Korkut Ata Universitesi	0.0004
Erciyes Universitesi	0.0105	Ozyegin Universitesi	0.0003
Erzincan Binali Yildirim Universitesi	0.0053	Pamukkale Universitesi	0.0198
Erzurum Teknik Universitesi	0.0015	Piri Reis Universitesi	0.0001
Eskisehir Osmangazi Universitesi	0.0129	Recep Tayyip Erdogan Universitesi	0.0054
Firat Universitesi	0.0033	**Sabanci Universitesi**	0.0024
Galatasaray Universitesi	0.0027	Sakarya Universitesi	0.0157
Gazi Universitesi	0.0228	Selcuk Universitesi	0.0161
Gaziantep Universitesi	0.0145	Sirnak Universitesi	0.0043
Giresun Universitesi	0.0118	Sivas Cumhuriyet Universitesi	0.0105
Gumushane Universitesi	0.0094	Suleyman Demirel Universitesi	0.0166
Hacettepe Universitesi	0.0117	TED Universitesi	0.0003
Harran Universitesi	0.0094	Tekirdag Namik Kemal Universitesi	0.0018
Hasan Kalyoncu Universitesi	0.0005	TOBB Ekonomi ve Teknoloji Universitesi	0.0037
Hatay Mustafa Kemal Universitesi	0.0073	Toros Universitesi	0.0005
Hitit Universitesi	0.0118	Trakya Universitesi	0.0130
Igdir Universitesi	0.0006	Uludag Universitesi	0.0281
Ihsan Dogramaci Bilkent Universitesi	0.0094	Usak Universitesi	0.0073
Inonu Universitesi	0.0116	Yalova Universitesi	0.0028
Isik Universitesi	0.0008	Yasar Universitesi	0.0016
Istanbul Aydin Universitesi	0.0047	Yeditepe Universitesi	0.0032
Istanbul Bilgi Universitesi	0.0093	Yildiz Teknik Universitesi	0.0159
Istanbul Gelisim Universitesi	0.0003	Yozgat Bozok Universitesi	0.0091
Istanbul Kultur Universitesi	0.0054	Zonguldak Bulent Ecevit Universitesi	0.0129

Notes: The underlined universities are the "elite" ones.

Table 2: Summary statistics

	All sample			**Males**			**Females**		
Variable	All	Elite	Non-elite	All	Elite	Non-elite	All	Elite	Non-elite
# of observations	44,950	1,675	43,275	20,248	835	19,413	24,702	840	23,862
Log real wage	1.892	2.173	1.881	1.921	2.140	1.912	1.868	2.206	1.856
Honors degree	0.149	0.330	0.142	0.122	0.286	0.115	0.172	0.373	0.164
GPA	2.60	2.76	2.59	2.55	2.70	2.55	2.63	2.83	2.63
Elite	0.037	1.000	0.000	0.041	1.000	0.000	0.034	1.000	0.000
Male	0.450	0.497	0.448	1.000	1.000	1.000	0.000	0.000	0.000
Age	24.44	24.23	24.44	24.78	24.46	24.79	24.15	24.01	24.16
Metropolitan prov.	0.516	0.923	0.500	0.528	0.905	0.511	0.506	0.941	0.491
Year of graduation									
2014	0.225	0.231	0.225	0.229	0.226	0.229	0.222	0.236	0.222
2015	0.227	0.215	0.228	0.232	0.214	0.233	0.224	0.216	0.224
2016	0.228	0.211	0.228	0.220	0.207	0.220	0.234	0.214	0.235
2017	0.195	0.211	0.194	0.192	0.208	0.191	0.197	0.214	0.196
2018	0.125	0.132	0.125	0.127	0.144	0.127	0.124	0.120	0.124
Year of labor market entry									
2014	0.124	0.228	0.120	0.135	0.242	0.130	0.116	0.214	0.112
2015	0.158	0.177	0.157	0.151	0.167	0.150	0.164	0.187	0.163
2016	0.193	0.195	0.193	0.189	0.184	0.189	0.196	0.207	0.195
2017	0.259	0.220	0.261	0.252	0.232	0.253	0.265	0.209	0.267
2018	0.266	0.180	0.270	0.274	0.176	0.278	0.260	0.183	0.263

Figure 1: Histograms for GPAs

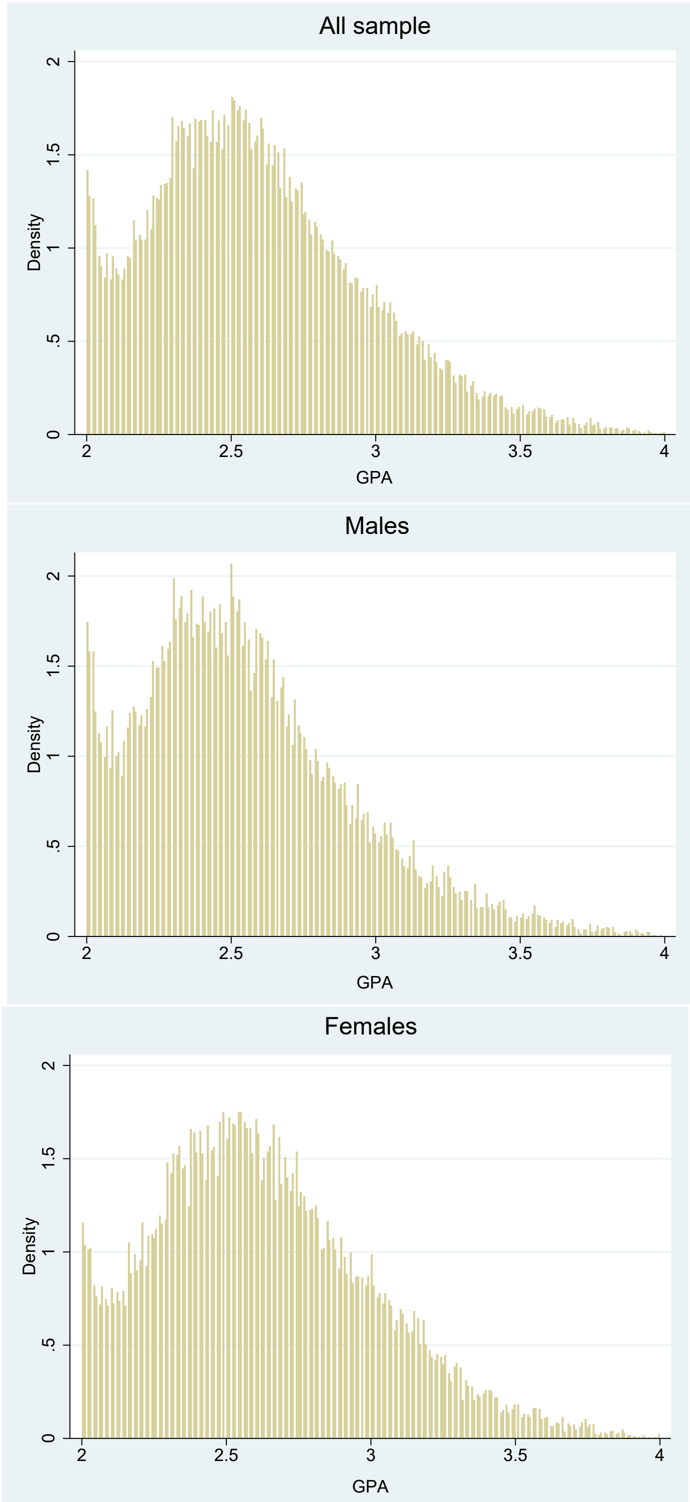


Figure 2: McCrary density test plots

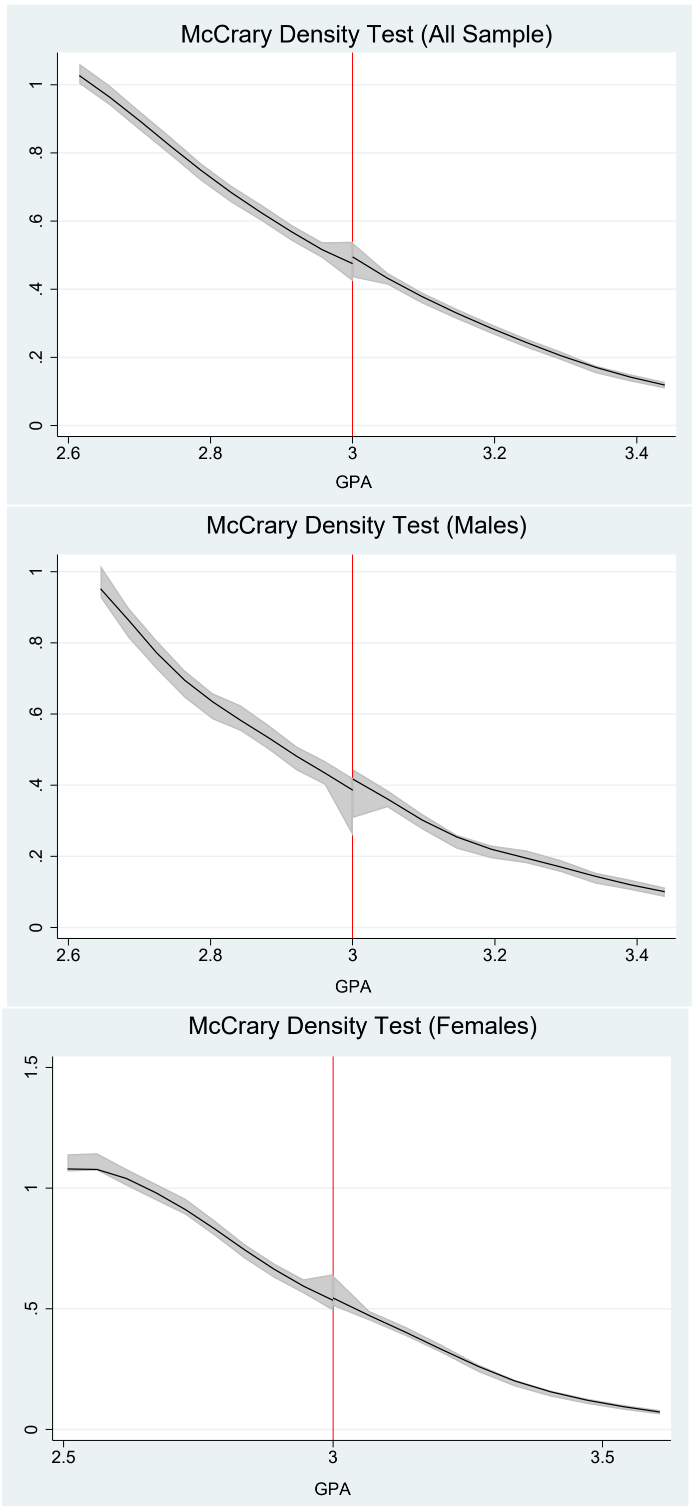


Table 3: McCrary density test statistics

Sample	p-value	# of observations
All sample	0.610	45,191
Males	0.346	20,325
Females	0.594	24,866
All sample (elite)	0.377	1,689
Males (elite)	0.106	840
Females (elite)	0.788	849
All sample (non-elite)	0.764	43,502
Males (non-elite)	0.449	19,485
Females (non-elite)	0.608	24,017

Notes: The testing procedure developed by Cattaneo et al. (2020) is implemented to perform the McCrary (2008) density test.

Figure 3: Covariate balance (visual evidence)

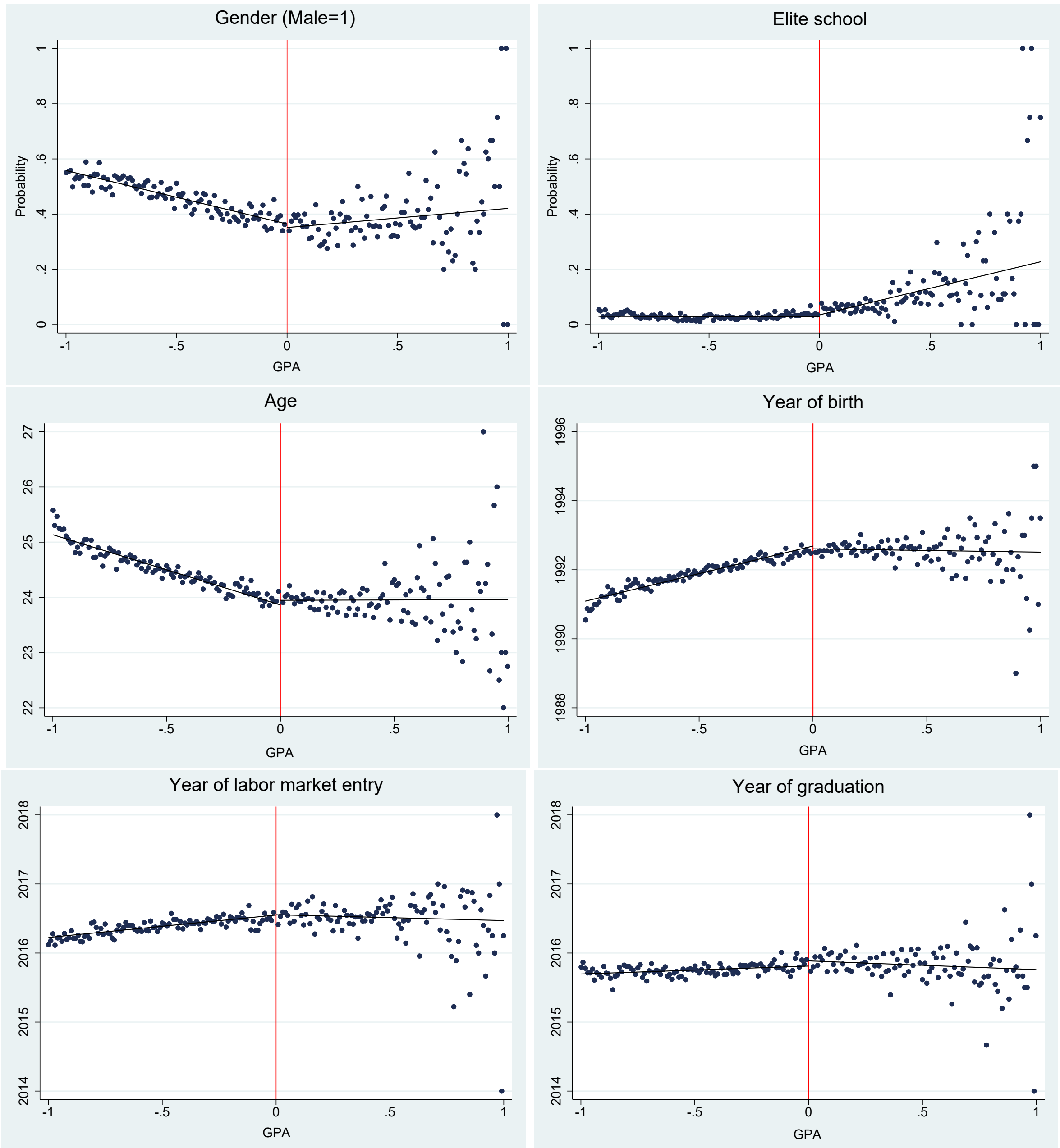


Table 4: Tests of covariate balance (RD estimations)

Kernel	Triangular	Uniform	Triangular	Uniform
Bandwidth selection procedure	CCT	CCT	IK	IK
Gender (Male=1, Female=0)	0.022	0.016	-0.004	-0.001
s.e.	(0.026)	(0.022)	(0.015)	(0.015)
p-value	(0.387)	(0.476)	(0.771)	(0.932)
Age	0.105	0.147	0.056	0.049
s.e.	(0.073)	(0.076)	(0.050)	(0.052)
p-value	(0.148)	(0.101)	(0.263)	(0.339)
Elite school (=1, 0 otherwise)	0.019	0.020	0.019	0.013
s.e.	(0.013)	(0.014)	(0.013)	(0.009)
p-value	(0.143)	(0.130)	(0.144)	(0.164)
Year of birth	-0.138	-0.093	-0.008	0.005
s.e.	(0.100)	(0.088)	(0.051)	(0.052)
p-value	(0.168)	(0.292)	(0.877)	(0.930)
Year of graduation	-0.101	0.008	0.024	0.030
s.e.	(0.077)	(0.054)	(0.043)	(0.044)
p-value	(0.187)	(0.881)	(0.583)	(0.503)
Year of labor market entry	-0.058	0.034	0.044	0.047
s.e.	(0.077)	(0.057)	(0.038)	(0.038)
p-value	(0.453)	(0.558)	(0.238)	(0.224)

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT and IK refer to the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012), respectively. Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Figure 4: RD plots—all sample

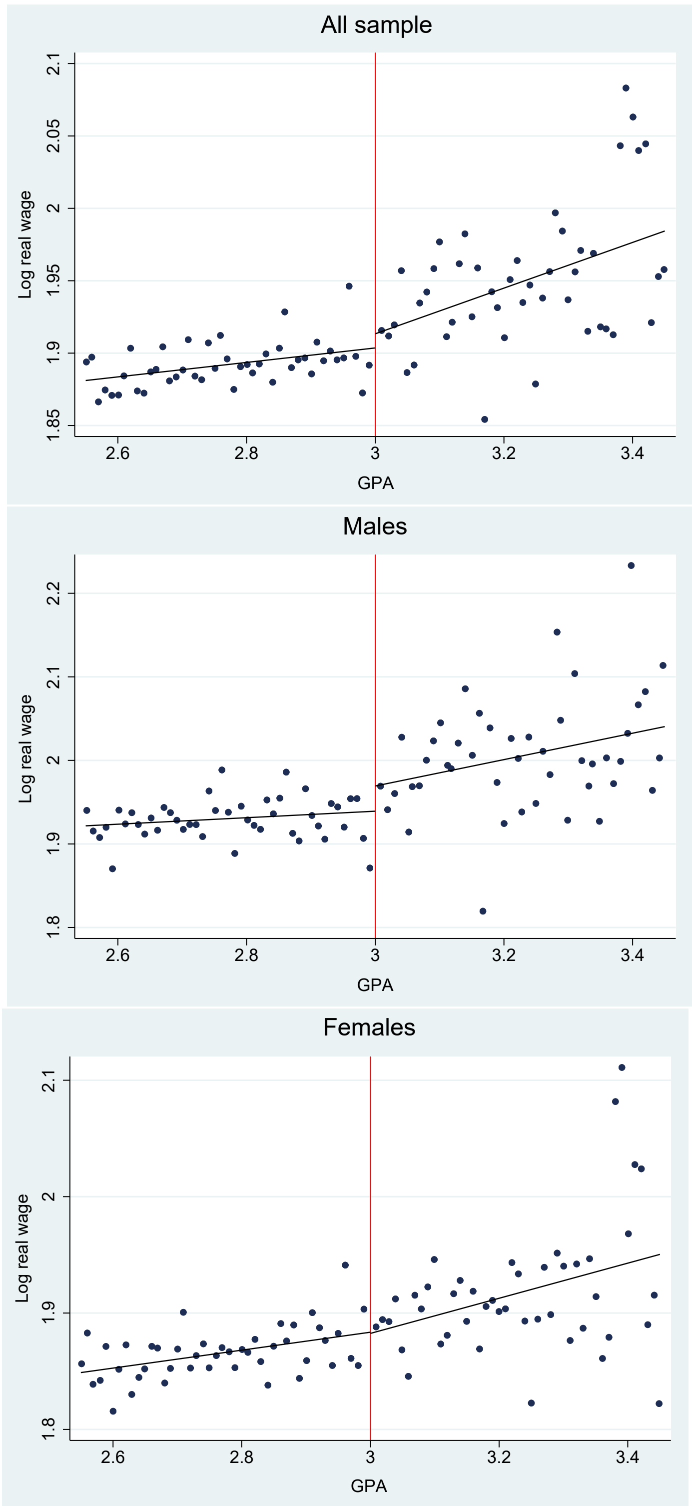


Figure 5: RD plots—elite schools

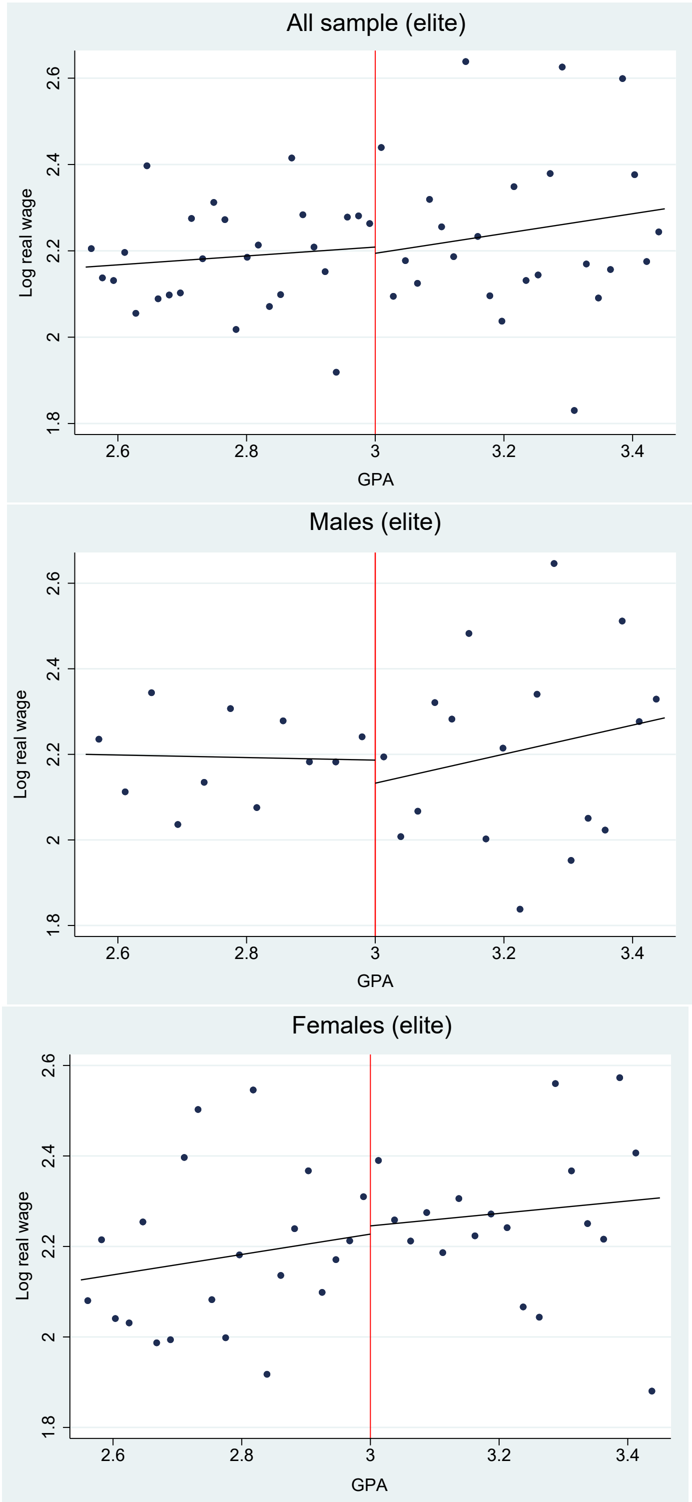


Figure 6: RD plots—non-elite schools

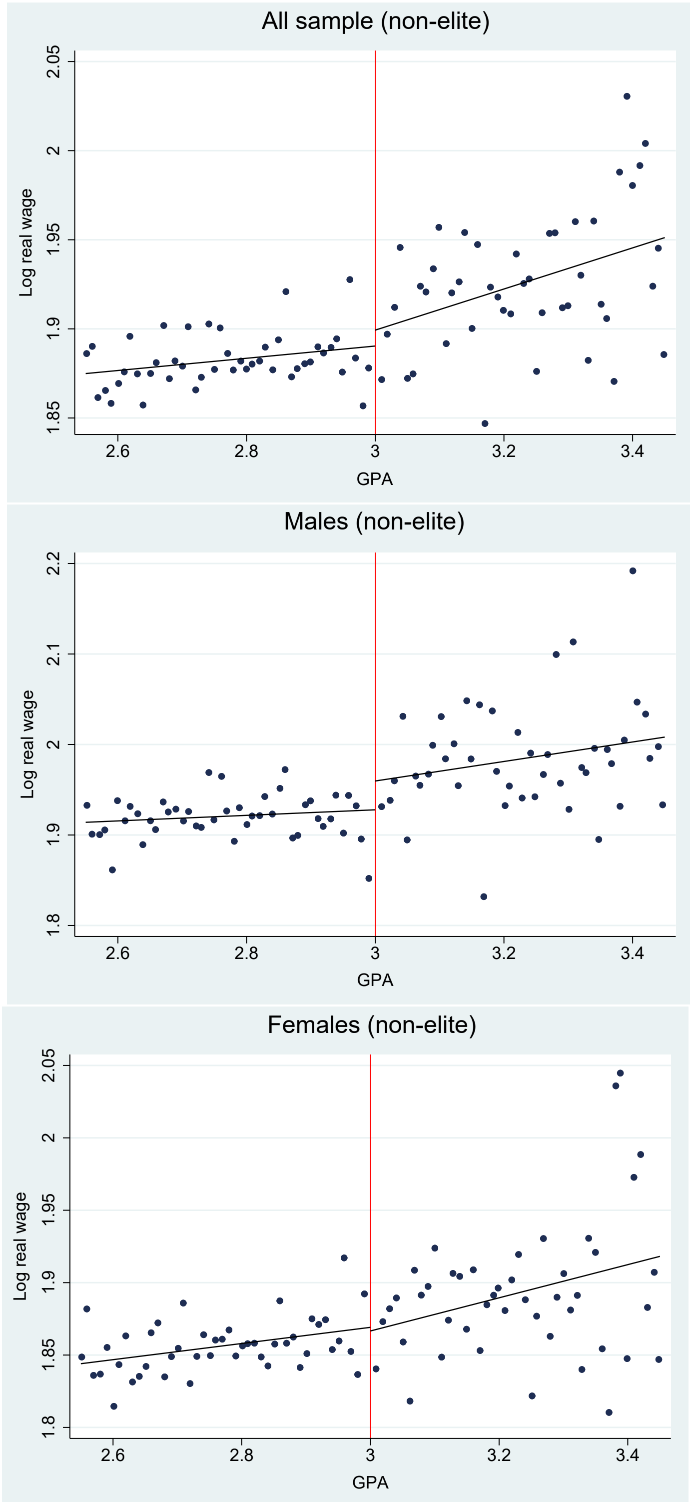


Table 5: Local linear RD estimates with robust inference

(Dependent variable: Natural log of real wage)

All sample				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.019	0.019	0.014	0.006
s.e.	(0.013)	(0.013)	(0.009)	(0.010)
p-value	(0.137)	(0.140)	(0.138)	(0.521)
Optimal bandwidth	0.277	0.221	0.556	0.437
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	44,950	44,950	44,950	44,950
Males				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.041*	0.050**	0.033**	0.030*
s.e.	(0.023)	(0.023)	(0.016)	(0.017)
p-value	(0.074)	(0.032)	(0.040)	(0.067)
Optimal bandwidth	0.257	0.219	0.561	0.440
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	20,248	20,248	20,248	20,248
Females				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.003	0.005	0.002	0.004
s.e.	(0.016)	(0.017)	(0.012)	(0.012)
p-value	(0.847)	(0.756)	(0.904)	(0.743)
Optimal bandwidth	0.294	0.191	0.484	0.380
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	24,702	24,702	24,702	24,702

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT and IK refer to the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012), respectively. Robust bias-corrected standard errors (and the associated *p*-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Table 6: Local linear RD estimates with robust inference (elite schools)

(Dependent variable: Natural log of real wage)

All sample (elite schools)				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	-0.004	0.011	-0.007	-0.014
s.e.	(0.095)	(0.088)	(0.054)	(0.055)
p-value	(0.965)	(0.899)	(0.892)	(0.795)
Optimal bandwidth	0.281	0.268	0.889	0.698
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	1,675	1,675	1,675	1,675
Males (elite schools)				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	-0.163	-0.191	-0.068	-0.026
s.e.	(0.130)	(0.137)	(0.096)	(0.101)
p-value	(0.210)	(0.163)	(0.477)	(0.797)
Optimal bandwidth	0.311	0.224	0.567	0.446
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	835	835	835	835
Females (elite schools)				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.110	0.097	0.042	0.015
s.e.	(0.135)	(0.115)	(0.094)	(0.096)
p-value	(0.412)	(0.400)	(0.654)	(0.877)
Optimal bandwidth	0.273	0.293	0.502	0.394
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	840	840	840	840

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT and IK refer to the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012), respectively. Robust bias-corrected standard errors (and the associated *p*-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Table 7: Local linear RD estimates with robust inference (non-elite schools)

(Dependent variable: Natural log of real wage)

All sample (non-elite schools)				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.008	0.013	0.013	0.011
s.e.	(0.013)	(0.013)	(0.008)	(0.008)
p-value	(0.552)	(0.323)	(0.118)	(0.178)
Optimal bandwidth	0.233	0.210	0.667	0.524
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	43,275	43,275	43,275	43,275
Males (non-elite schools)				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.043*	0.039	0.035**	0.029*
s.e.	(0.024)	(0.026)	(0.015)	(0.015)
p-value	(0.076)	(0.133)	(0.016)	(0.056)
Optimal bandwidth	0.216	0.161	0.672	0.528
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	19,413	19,413	19,413	19,413
Females (non-elite schools)				
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	-0.010	-0.004	0.001	0.002
s.e.	(0.015)	(0.014)	(0.010)	(0.010)
p-value	(0.499)	(0.771)	(0.944)	(0.844)
Optimal bandwidth	0.271	0.246	0.638	0.501
Bandwidth selection procedure	CCT	CCT	IK	IK
# of observations	23,862	23,862	23,862	23,862

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT and IK refer to the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) and Imbens and Kalyanaraman (2012), respectively. Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Figure 7: The main RD effect (visual evidence)

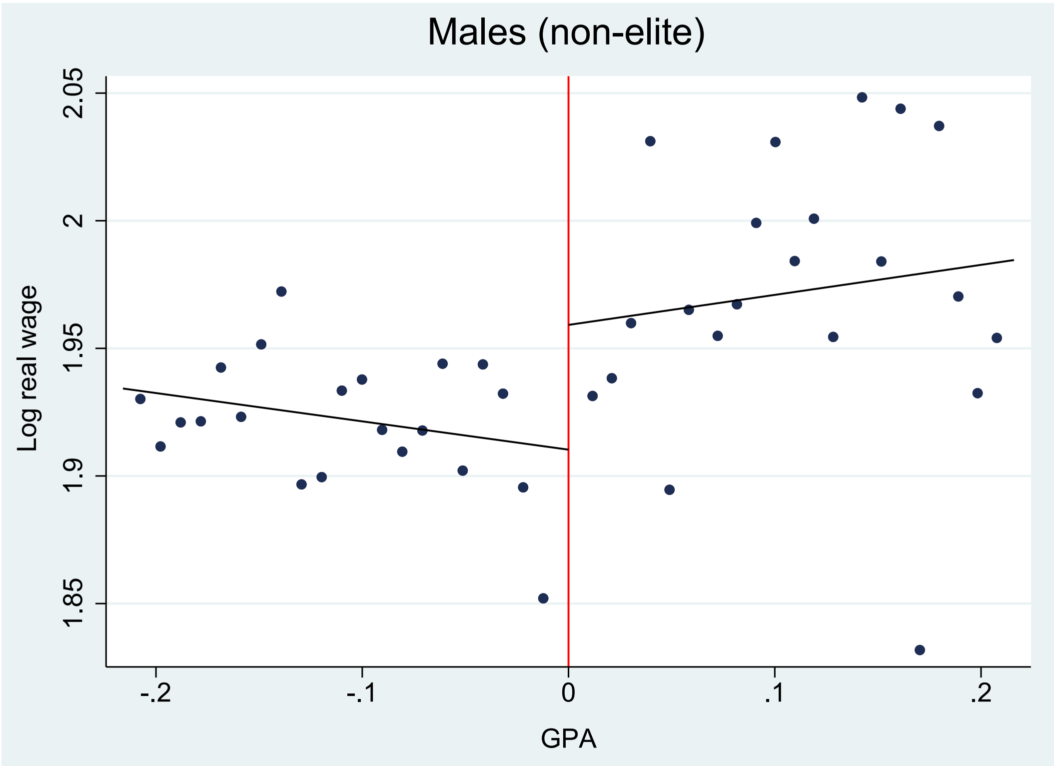
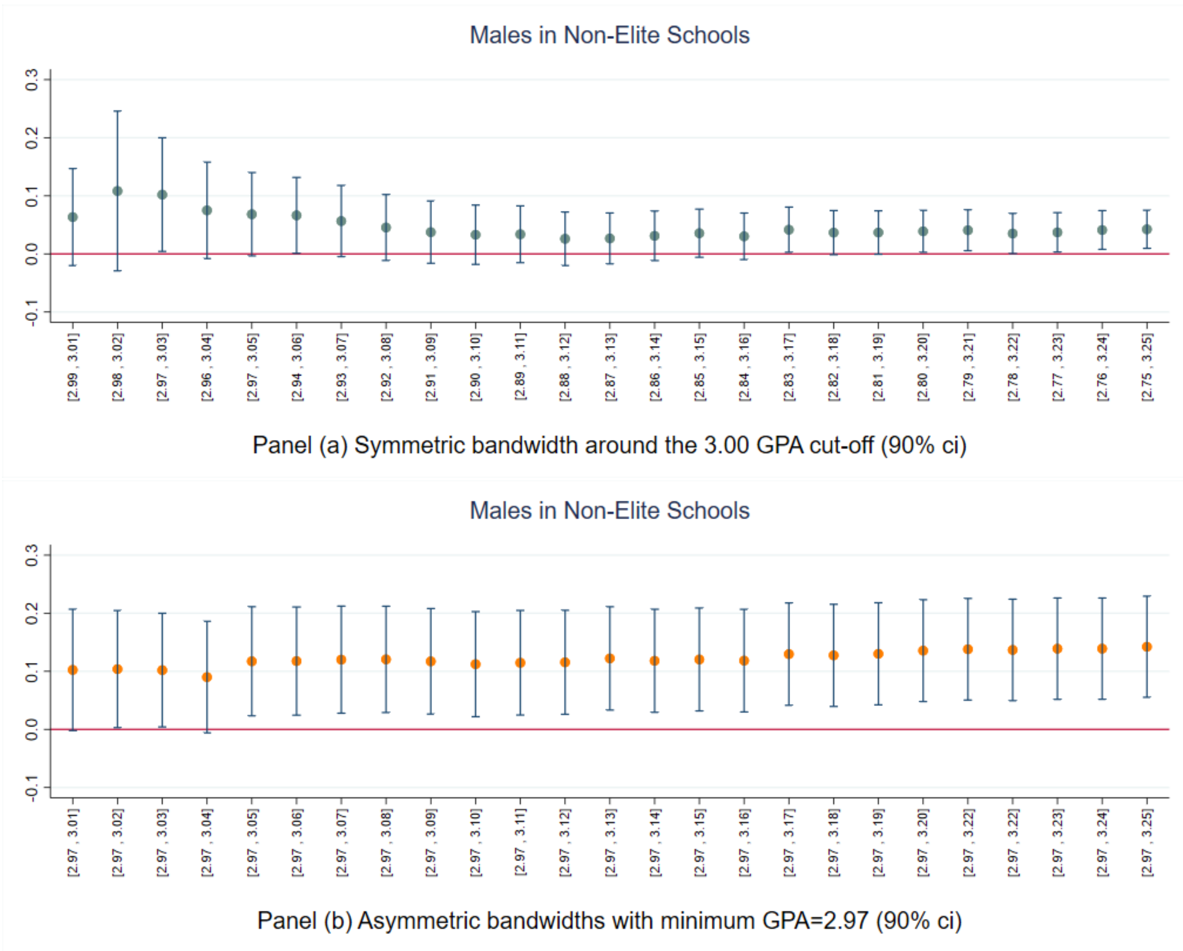
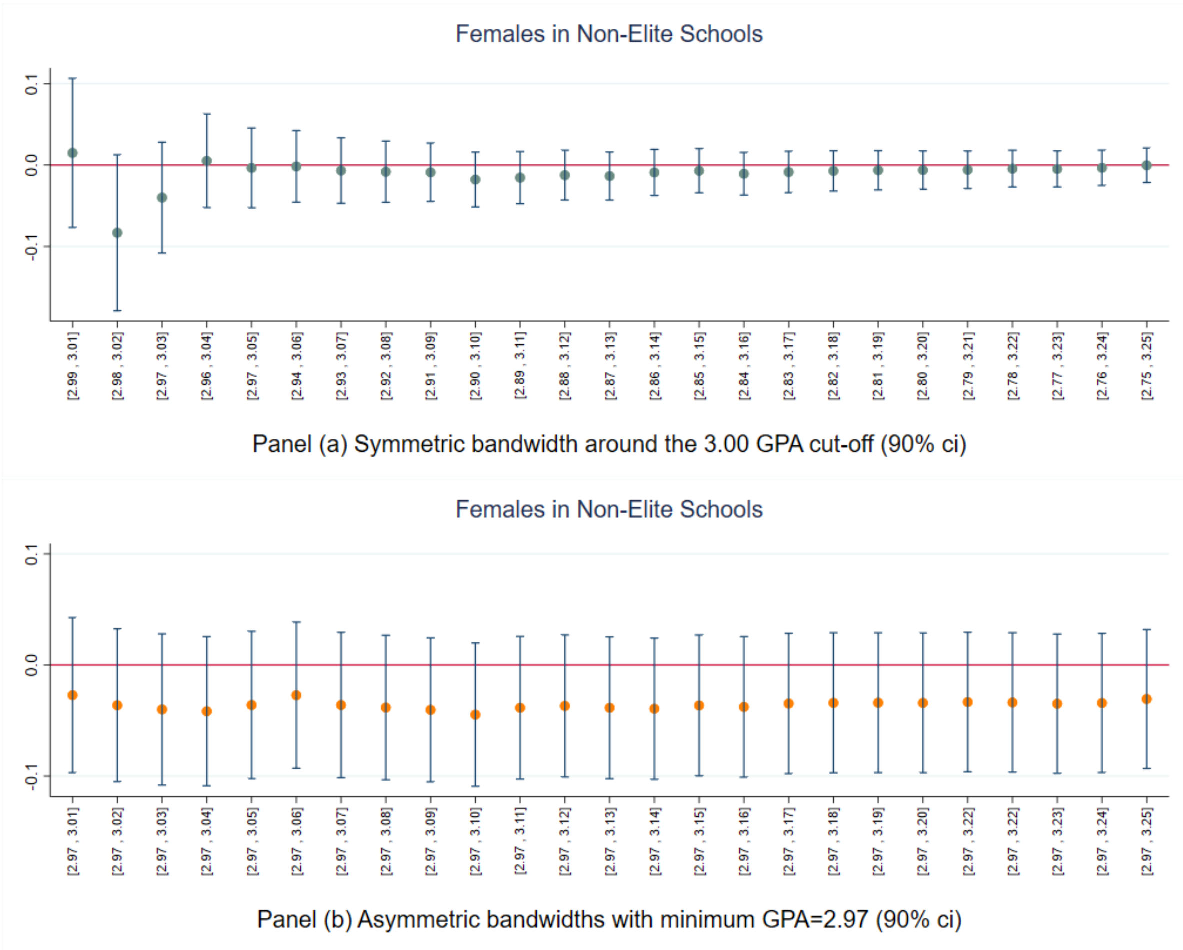


Figure 8: Manual bandwidth estimates for males from non-elite universities



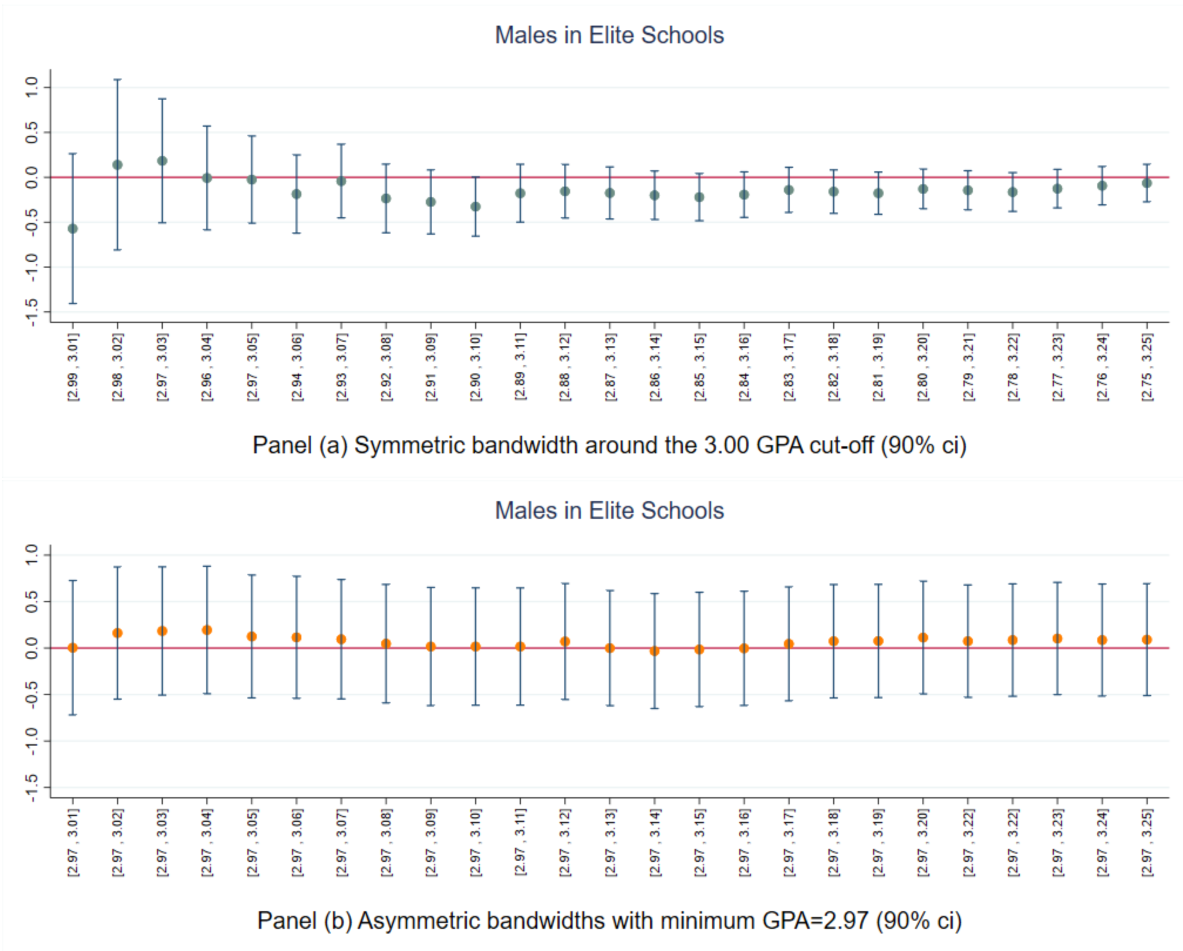
Notes: The panels show the coefficient estimates of manual RD regressions of log real wages on the GPA cutoff. The cutoff is a dummy variable indicating whether GPA is equal to or higher than 3. The specification includes the distance to cutoff and the interaction between the distance and the cutoff dummy.

Figure 9: Manual bandwidth estimates for females from non-elite universities



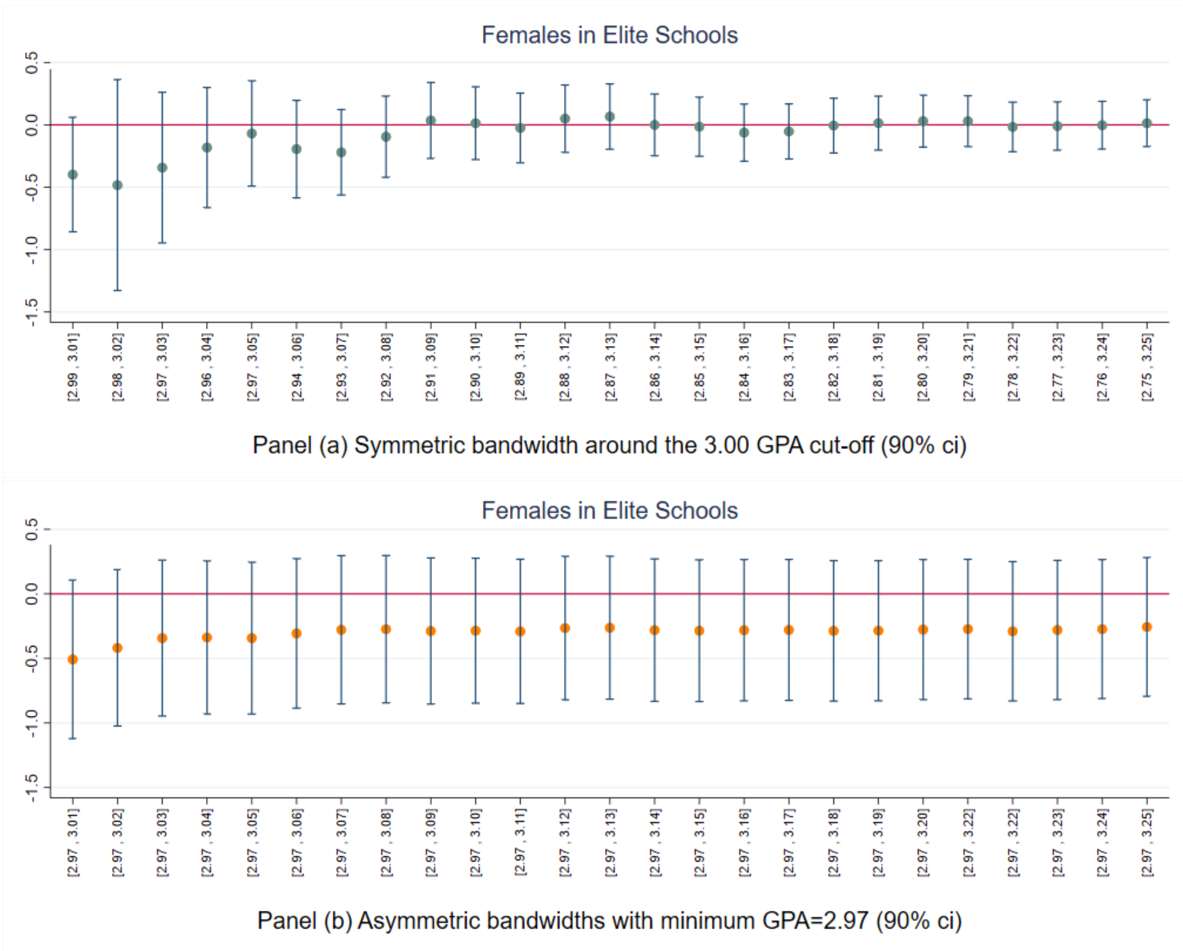
Notes: The panels show the coefficient estimates of manual RD regressions of log real wages on the GPA cutoff. The cutoff is a dummy variable indicating whether GPA is equal to or higher than 3. The specification includes the distance to cutoff and the interaction between the distance and the cutoff dummy.

Figure 10: Manual bandwidth estimates for males from elite universities



Notes: The panels show the coefficient estimates of manual RD regressions of log real wages on the GPA cutoff. The cutoff is a dummy variable indicating whether GPA is equal to or higher than 3. The specification includes the distance to cutoff and the interaction between the distance and the cutoff dummy.

Figure 11: Manual bandwidth estimates for females from elite universities



Notes: The panels show the coefficient estimates of manual RD regressions of log real wages on the GPA cutoff. The cutoff is a dummy variable indicating whether GPA is equal to or higher than 3. The specification includes the distance to cutoff and the interaction between the distance and the cutoff dummy.

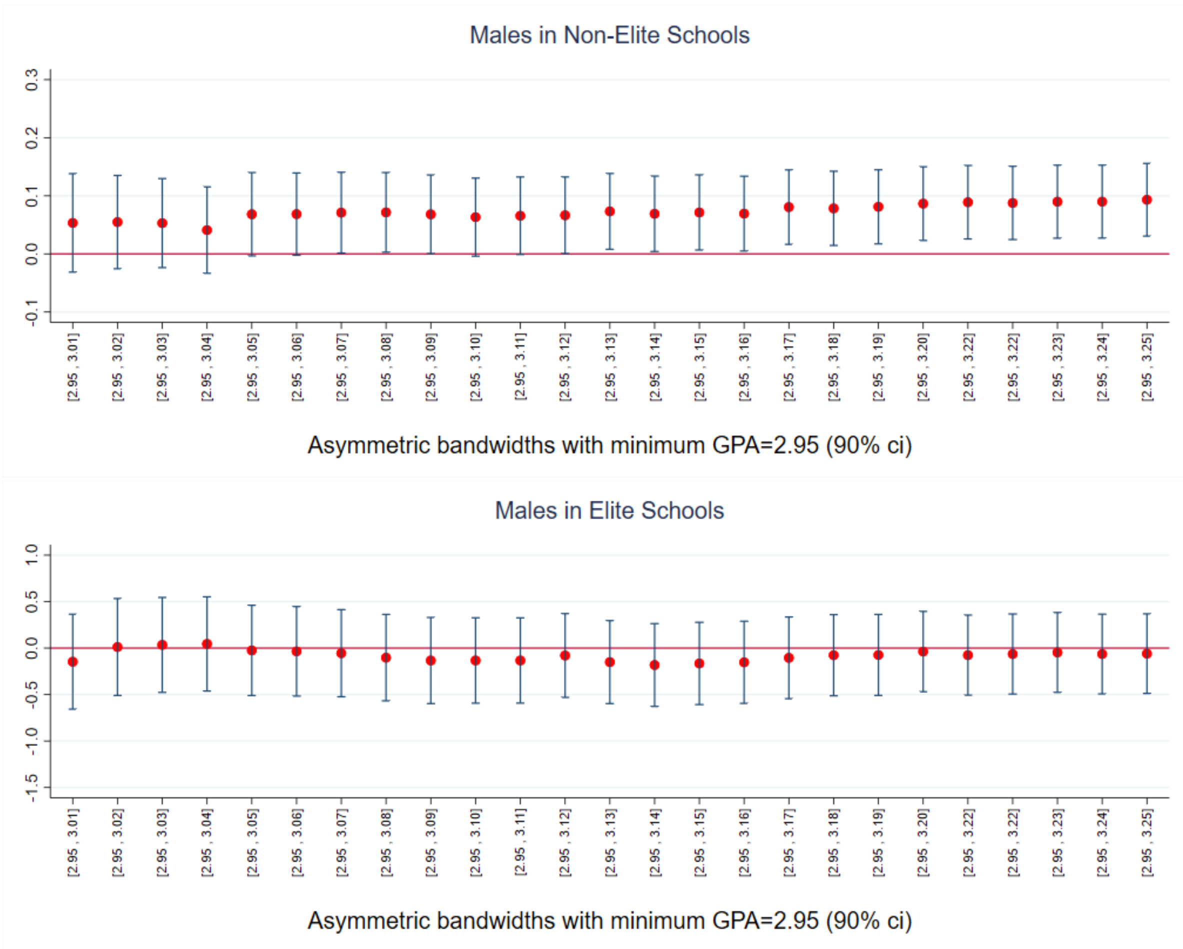
Impact of graduating with honors on entry wages of economics majors

Appendix

By Salim Atay, Gunes A. Asik, and Semih Tumen

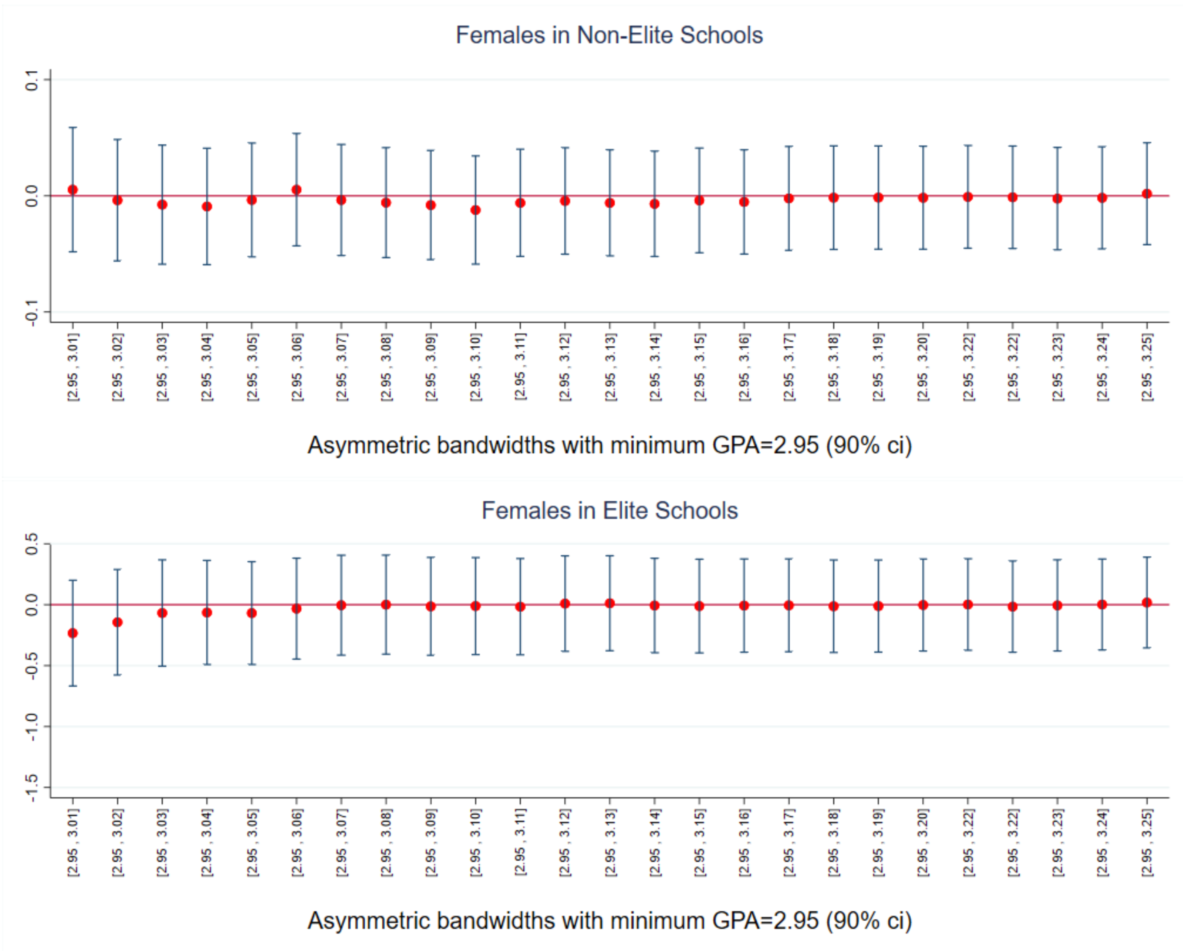
A Additional figures and tables

Figure A1: Robustness check for asymmetric manual bandwidth, males



Notes: The panels show the coefficient estimates of manual RD regressions of log real wages on the GPA cutoff. The cutoff is a dummy variable indicating whether GPA is equal to or higher than 3. The specification includes the distance to cutoff and the interaction between the distance and the cutoff dummy.

Figure A2: Robustness check for asymmetric manual bandwidth, females



Notes: The panels show the coefficient estimates of manual RD regressions of log real wages on the GPA cutoff. The cutoff is a dummy variable indicating whether GPA is equal to or higher than 3. The specification includes the distance to cutoff and the interaction between the distance and the cutoff dummy.

Table A1: RD results for the STEM fields

(Dependent variable: Natural log of real wage)

Males, elite schools		
Kernel	Triangular	Uniform
Honors degree	0.006	0.008
s.e.	(0.092)	(0.096)
p-value	0.94	0.93
Optimal bandwidth	0.412	0.307
# of observations	12,619	12,619
Females, elite schools		
Kernel	Triangular	Uniform
Honors degree	0.014	0.011
s.e.	(0.074)	(0.090)
p-value	0.86	0.90
Optimal bandwidth	0.456	0.507
# of observations	7,357	7,357
Males, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.002	0.002
s.e.	(0.017)	(0.017)
p-value	0.90	0.92
Optimal bandwidth	0.449	0.312
# of observations	151,794	151,794
Females, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.015	0.017
s.e.	(0.012)	(0.012)
p-value	0.20	0.14
Optimal bandwidth	0.251	0.181
# of observations	160,918	160,918

Notes: STEM fields include engineering, life sciences, and other fields such as physics, mathematics, and chemistry. Engineering includes bachelor's degrees in electronics, computer, industrial, structural, petroleum, geology, geophysics, aerospace, food, topographical, metallurgical and materials, textiles, automobile, manufacturing, environmental, biotechnology, and naval engineering. Life sciences include genetics, molecular biology, bio-informatics, pharmacology, physiotherapy and rehabilitation, and nursery. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. The optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) (CCT) are used in the estimations. Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Table A2: Impact by university establishment date

(Dependent variable: Natural log of real wage)

	Males, non-elite schools			
Establishment date	1933-2005		After 2006	
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	0.068*	0.073*	-0.016	0.001
s.e.	(0.037)	(0.037)	(0.039)	(0.044)
p-value	0.06	0.053	0.69	0.98
Optimal bandwidth	0.288	0.235	0.254	0.175
Bandwidth selection procedure	CCT	CCT	CCT	CCT
# of observations	15,166	15,166	4,319	4,319
	Females, non-elite schools			
Establishment date	1933-2005		After 2006	
Kernel	Triangular	Uniform	Triangular	Uniform
Honors degree	-0.006	0.002	-0.021	-0.009
s.e.	(0.027)	(0.024)	(0.024)	(0.024)
p-value	0.83	0.93	0.38	0.72
Optimal bandwidth	0.317	0.276	0.178	0.173
Bandwidth selection procedure	CCT	CCT	CCT	CCT
# of observations	18,134	18,134	5,883	5,883

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT refers to the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017). Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

B Testing the sensitivity of the estimates to the observations at the threshold (the Donut approach)

As an additional robustness check, we test whether our estimates are sensitive to the observations at the threshold. The RD designs basically compare the means as the estimates approach the threshold from each side; therefore, the estimates should not be sensitive to the observations at the threshold (Barreca et al., 2011). To perform this test, we rely on a donut RD design where we drop the observations clustered around the 3.00 cutoff. Barreca et al. (2011) and Barreca et al. (2016) show that the donut RD designs outperform the standard RD specification in contexts with heaping in the running variable density as spikes. Although there is no obvious concern in our setting about a potential heaping at the threshold, the donut hole approach is still a useful additional test to convince the reader that the results are not driven by the asymmetric distribution of observations around the threshold.

Hence, in this exercise, we check whether our results are robust to excluding the potential, non-random spikes around the exact 3.00 cutoff. We first run our donut estimations by dropping observations with -0.01 to +0.01 points around the 3.00 cutoff, i.e., graduates with GPA between 2.99 and 3.01. We then drop observations with -0.05 to +0.05 points and -0.1 to +0.1 points around 3.00 cutoff one by one. The results in Table A3 show that our findings are robust to dropping observations around the cutoff. In particular, it is reassuring that dropping observations with GPAs around 2.99 and 3.01 gives almost identical coefficients as before for males of non-elite university graduates, as this bandwidth is exactly where one would expect that a potential rounding or manipulation would occur.

Table A3: Donut RD estimates, non-elite schools

(Dependent variable: Natural log of real wage)

Males, non-elite schools			
	Donut, 0.01	Donut, 0.05	Donut, 0.1
Honors degree	0.0387**	0.0295	0.133*
s.e.	(0.0193)	(0.0254)	(0.0767)
p-value	0.045	0.244	0.082
# of observations	19,271	18,805	18,035
Females, non-elite schools			
	Donut, 0.01	Donut, 0.05	Donut, 0.1
Honors degree	0.0039	-0.0018	0.0883
s.e.	(0.0149)	(0.0225)	(0.0758)
p-value	0.794	0.936	0.244
# of observations	23,596	22,837	21,566
Males, elite schools			
	Donut, 0.01	Donut, 0.05	Donut, 0.1
Honors degree	-0.2860*	-0.0646	0.0713
s.e.	(0.149)	(0.174)	(0.203)
p-value	0.055	0.711	0.725
# of observations	825	800	753
Females, elite schools			
	Donut, 0.01	Donut, 0.05	Donut, 0.1
Honors degree	0.0227	0.0039	0.0074
s.e.	(0.104)	(0.121)	(0.180)
p-value	0.827	0.974	0.967
# of observations	826	788	734

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. The optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) (CCT) are used in the estimations. Robust bias-corrected standard errors are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors. The triangular kernel is used in all estimations.

C Results for good jobs

In an effort to understand the sources of variation more clearly, we use the International Standard Classification of Occupations, i.e., ISCO-08 codes of the International Labour Organization (ILO) provided in the administrative data. The ISCO-08 codes are broadly classified between 0 and 9; 0=armed forces, 1=managerial positions, 2=professionals, 3=technicians, and associate professionals, 4=clerical support workers, 5=services and sales workers, 6=craft and related occupations, 7=skilled agricultural workers, 8=plant and machine operators, and 9=elementary occupations. ILO (2012) and ILO (2018) map skill requirements of occupations with the International Standard Classification of Education (ISCED) codes.

According to these classifications, occupational codes starting with 1 and 2—i.e., managerial positions and professional occupations—require a tertiary education degree. These are mostly white-collar jobs requiring a university degree. ILO (2018) explains that occupations starting with 1 and 2 involve "extended levels of literacy, numeracy, excellent interpersonal communication skills, problem-solving, decision-making, and creativity," and require ISCED (2012) formal education categories of 6 to 8, which is at a minimum a bachelor's degree. On the other hand, the match of a university graduate with occupations starting with ISCO-08 codes 3 to 9 indicates that there is a qualification mismatch, i.e., the individual is over-educated for the position placed.[1] Hence, the occupations starting with 1 and 2 can be considered as jobs with appropriate skill matching, and we refer to them as "good jobs" as a short-cut for no skill mismatch. It should be noted that there can be other sources of mismatches, such as those stemming from incompatibility between the socio-emotional skills of individuals and job requirements, however, we are unable to capture these in the administrative data and our "good jobs" definition only involves the matches based on tertiary degree categories.

Using these classifications, we restrict our sample to graduates landing to occupations starting with ISCO-08 codes of 1 and 2, and only in the top 10 metropolitan provinces of Türkiye consisting of Istanbul, Ankara, Izmir, Kocaeli, Bursa, Konya, Antalya, Adana, Gaziantep, and Mersin. According to Turkish Administrative Law, metropolitan provinces are those in which the central city administration is subdivided into districts, where each district includes a corresponding district municipality. These provinces typically have a minimum population of 1 million. The motivation behind focusing on large provinces is that most of the private sector and large companies are located in these large provinces. The official statistics (by the Turkish Statistical Institute—TurkStat) show that, as of 2018, these 10 provinces alone contributed to 65 percent of the national GDP in Türkiye. In Table A4, we increase the number of provinces to include the richest 20 provinces; and, in Table A5, we include all 81 provinces of Türkiye. We also focus on graduates placed in managerial or professional occupations, because these are the type of jobs that are suitable for university graduates in terms of skills acquired and that pay competitive

[1] The highest skill mismatch is for occupations starting with 9 as these are elementary jobs.

wages.[2] We do not include job matches starting with ISCO-08 codes 3 (technicians and associate professionals), because these jobs require a shorter cycle of tertiary education such as a two-year higher education diploma, hence indicating a mild degree of mismatch for an individual with a four-year bachelor degree. Our results, however, are robust to including this sub-group.

To ensure that our results on good jobs are not driven by selection on outcomes, we first show that the recent graduates are not sorted into good jobs based on their GPA. In other words, we first show that there is no change in the probability of landing on a managerial or professional position in one of the largest 10 provinces at the 3.00 cutoff. In Table A6, we run RD estimations based on the Calonico et al. (2017) algorithm, where landing on a professional or managerial position in one of the 10 largest provinces is an outcome variable. As the Table shows, estimated coefficients are not significant for any of the groups, with large $p-$values. The results suggest that graduates with higher GPAs are not sorted into better urban jobs for any of the groups. Finally, before proceeding to our main results on starting wages for good jobs, we present the standard visual evidence in Figure A3. As the figure shows, there is a very clear discrete jump in the starting wages of males graduating from non-elite universities but not in the wages of females graduating from non-elite universities. In Figure A4, we display the corresponding plots for graduates of elite universities. As before, there is no discontinuity at the 3.00 cutoff for males or females.

Our estimations in Table A7 also confirm the visual evidence. For male graduates of non-elite universities, an honors degree leads to a staggering 39 percent ($e^{0.33}-1$) increase in starting wages in large provinces and in jobs with the right occupational skills match. The results using a uniform kernel function in the second column are almost identical. The optimal CCT bandwidths are between 0.292 and 0.207 points around the cutoff. As before, we find no effect on female graduates of non-elite universities. In the last two rows of Table A7, we run the estimations for elite universities. Once again, in line with the earlier results, we find an effect on neither males nor females of graduates of top universities. In Table A4, we increase the number of provinces to 20. These provinces produced about 78 percent of the total GDP of Türkiye in 2018, according to TurkStat's figures. The coefficient sizes and estimated optimal bandwidths are very similar and indicate an effect between 39 and 43 percent on starting wages for male graduates of non-elite universities. In Table A5, we include all provinces but focus only on job matches in managerial and professional occupations. Once again, we find that graduating with an honors degree leads to an increase in starting wages for male graduates of non-elite universities, but not for female graduates or for students graduating from top universities. The coefficient size is between 27 to 32 percent, smaller in comparison to similar jobs in metropolitan provinces, but still indicates an economically significant effect.

[2] Although it might seem odd that recent graduates land in managerial positions, our data based on the occupation codes shows that the majority of these occupations are in the retail and wholesales sector, such as sales managers, product managers, communications managers, restaurant managers, and store managers.

Table A4: Professional and managerial occupations at 20 largest provinces

(Dependent variable: Natural log of real wage)

Males, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.332***	0.364***
s.e.	(0.128)	(0.128)
p-value	(0.010)	(0.004)
Optimal bandwidth	0.265	0.220
# of observations	1,556	1,556
Females, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.042	0.041
s.e.	(0.066)	(0.065)
p-value	(0.524)	(0.519)
Optimal bandwidth	0.239	0.194
# of observations	2,468	2,468
Males, elite schools		
Kernel	Triangular	Uniform
Honors degree	-0.264	-0.229
s.e.	(0.266)	(0.287)
p-value	(0.321)	(0.424)
Optimal bandwidth	0.271	0.189
# of observations	229	229
Females, elite schools		
Kernel	Triangular	Uniform
Honors degree	0.2435	0.168
s.e.	(0.262)	(0.191)
p-value	(0.354)	(0.380)
Optimal bandwidth	0.257	0.329
# of observations	266	266

Notes: Provinces included in the estimations are Istanbul, Ankara, Izmir, Kocaeli, Bursa, Konya, Antalya, Adana, Gaziantep, Mersin, Tekirdag, Manisa, Kayseri, Hatay, Balikesir, Mugla, Sakarya, Eskisehir, Denizli, and Samsun. Managerial and professional occupations are those with ISCO-08 occupation codes starting with 1, and 2. ISCO-08 codes starting with 1 indicate employment in managerial positions, and 2 indicate employment in professional occupations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. The optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) (CCT) are used in the estimations. Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Table A5: Professional and managerial occupations: All (81) provinces

(Dependent variable: Natural log of real wage)

Males, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.235**	0.280**
s.e.	(0.114)	(0.115)
p-value	(0.039)	(0.015)
Optimal bandwidth	0.275	0.235
# of observations	2,011	2,011
Females, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.023	0.030
s.e.	(0.065)	(0.064)
p-value	(0.723)	(0.636)
Optimal bandwidth	0.236	0.188
# of observations	3,250	3,250
Males, elite schools		
Kernel	Triangular	Uniform
Honors degree	-0.267	-0.230
s.e.	(0.266)	(0.286)
p-value	(0.316)	(0.422)
Optimal bandwidth	0.270	0.189
# of observations	232	232
Females, elite schools		
Kernel	Triangular	Uniform
Honors degree	0.256	0.156
s.e.	(0.262)	(0.189)
p-value	(0.329)	(0.408)
Optimal bandwidth	0.253	0.325
# of observations	270	270

Notes: Managerial and professional occupations are those with ISCO-08 occupation codes starting with 1, and 2. ISCO-08 codes starting with 1 indicate employment in managerial positions, and 2 indicate employment in professional occupations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. The optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017) (CCT) are used in the estimations. Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Table A6: Professional and managerial occupations at 10 largest metropolitan provinces

(Dependent variable: Probability of taking a professional or managerial position)

Males, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	-0.0143	-0.0224
s.e.	(0.023)	(0.023)
p-value	(0.534)	(0.333)
Optimal bandwidth	0.202	0.164
Bandwidth selection procedure	CCT	CCT
# of observations	19,536	19,536
Females, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	-0.0105	-0.0065
s.e.	(0.0175)	(0.0193)
p-value	(0.549)	(0.735)
Optimal bandwidth	0.268	0.183
Bandwidth selection procedure	CCT	CCT
# of observations	24,028	24,028
Males, elite schools		
Kernel	Triangular	Uniform
Honors degree	-0.1542	-0.1168
s.e.	(0.141)	(0.144)
p-value	(0.275)	(0.416)
Optimal bandwidth	0.301	0.248
Bandwidth selection procedure	CCT	CCT
# of observations	843	843
Females, elite schools		
	Triangular	Uniform
Honors degree	-0.04935	-0.0276
s.e.	(0.1182)	(0.1271)
p-value	(0.677)	(0.828)
Optimal bandwidth	0.370	0.258
Bandwidth selection procedure	CCT	CCT
# of observations	849	849

Notes: Metropolitan provinces included in the estimations are Istanbul, Ankara, Izmir, Kocaeli, Bursa, Konya, Antalya, Adana, Gaziantep, and Mersin. Managerial and professional occupations are those with ISCO-08 occupation codes starting with 1, and 2. ISCO codes starting with 1 indicate employment in managerial positions, and 2 indicate employment in professional occupations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT refers to the optimal bandwidth selection procedures developed by Calonico et al. (2014, 2017). Robust bias-corrected standard errors (and the associated *p*-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.

Figure A3: Graduates of non-elite universities in professional and managerial occupations in 10 largest metropolitan provinces

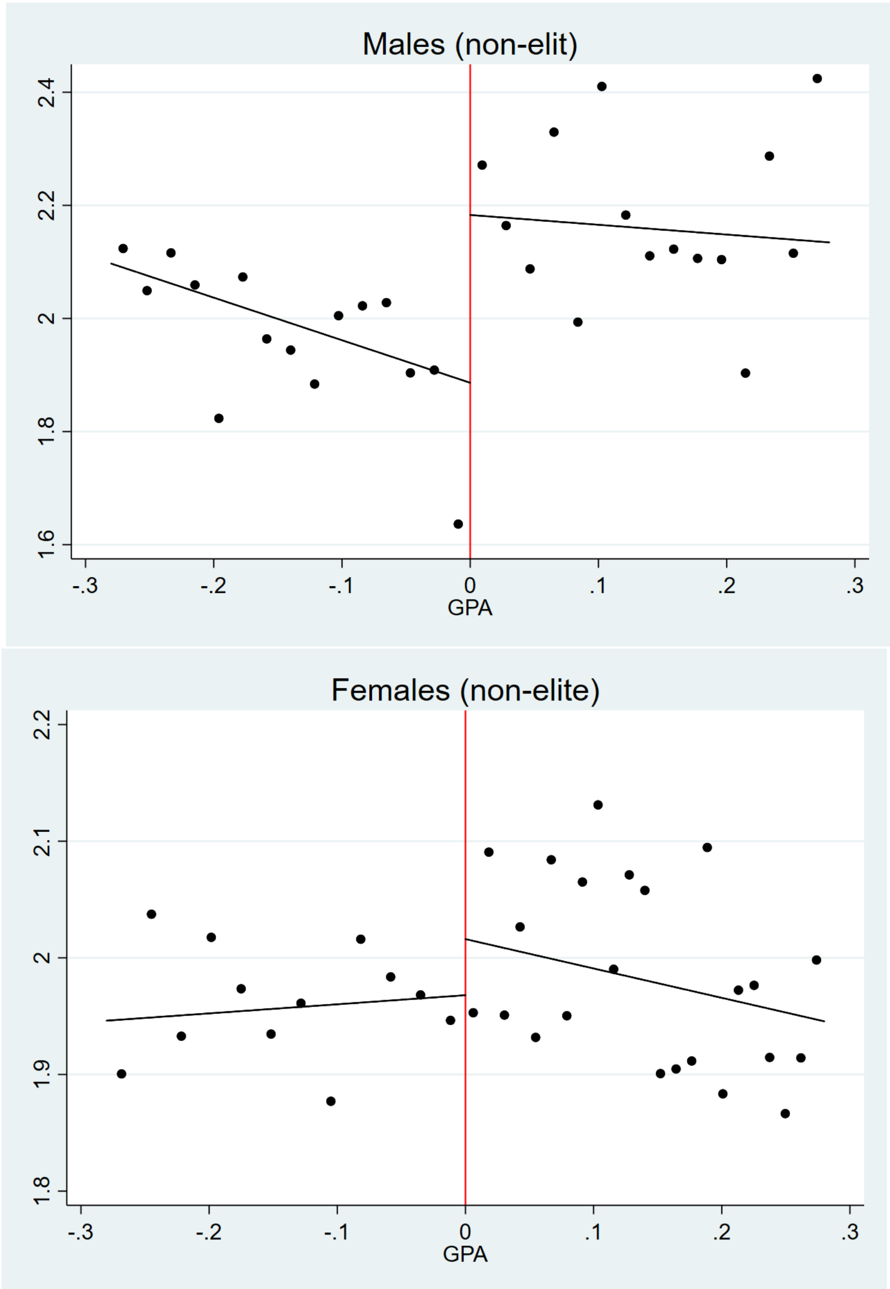


Figure A4: Graduates of elite universities in professional and managerial occupations in 10 largest metropolitan provinces

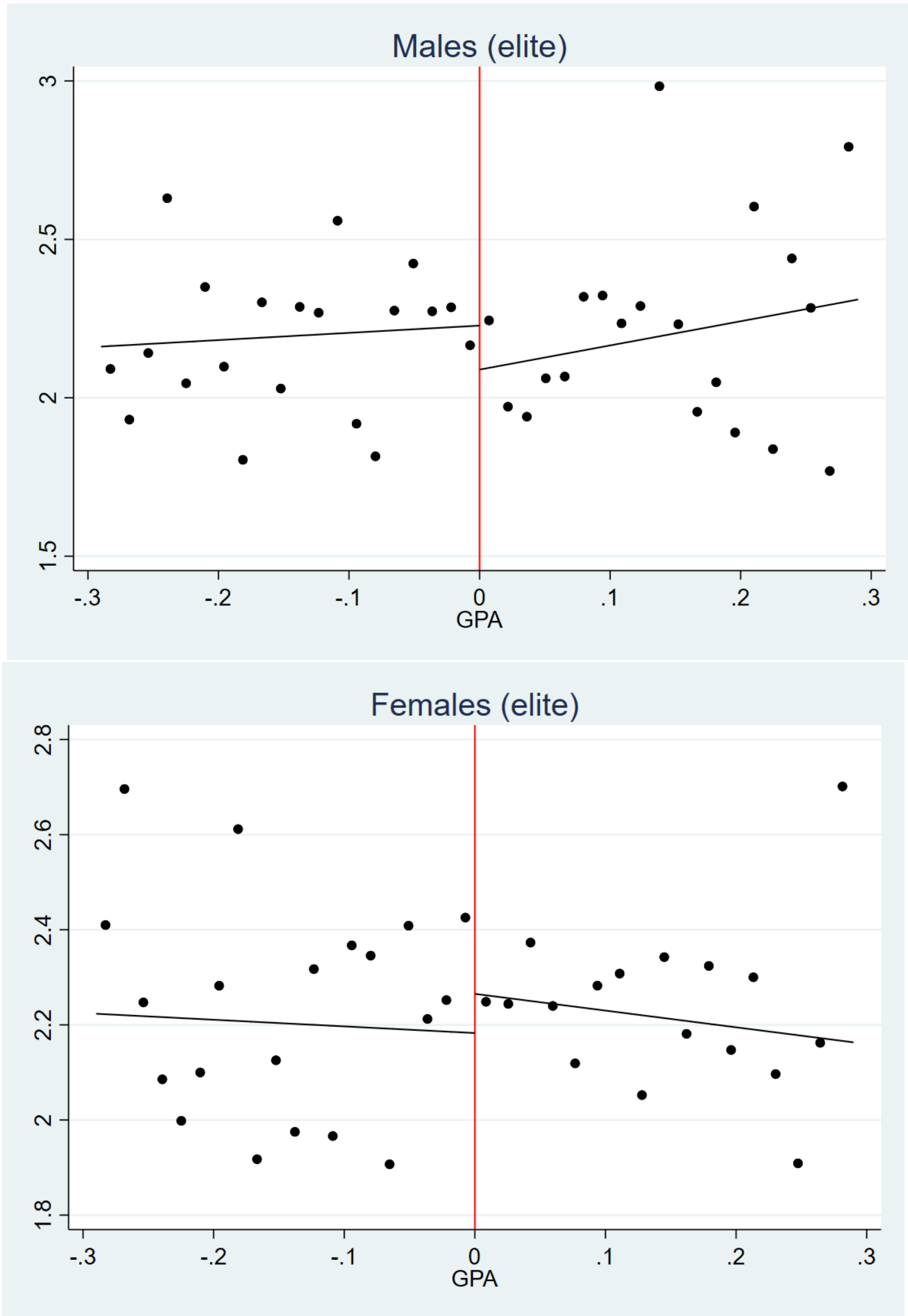


Table A7: Professional and managerial occupations at 10 largest metropolitan provinces

(Dependent variable: Natural log of real wage)

Males, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.336**	0.330**
s.e.	(0.129)	(0.145)
p-value	(0.009)	(0.023)
Optimal bandwidth	0.292	0.207
Bandwidth selection procedure	CCT	CCT
# of observations	1,411	1,411

Females, non-elite schools		
Kernel	Triangular	Uniform
Honors degree	0.057	0.072
s.e.	(0.077)	(0.0763)
p-value	(0.454)	(0.343)
Optimal bandwidth	0.222	0.169
Bandwidth selection procedure	CCT	CCT
# of observations	2,125	2,125

Males, elite schools		
Kernel	Triangular	Uniform
Honors degree	-0.255	-0.167
s.e.	(0.263)	(0.266)
p-value	(0.331)	(0.530)
Optimal bandwidth	0.279	0.250
Bandwidth selection procedure	CCT	CCT
# of observations	223	223

Females, elite schools		
Kernel	Triangular	Uniform
Honors degree	0.195	0.135
s.e.	(0.279)	(0.208)
p-value	(0.484)	(0.518)
Optimal bandwidth	0.276	0.350
Bandwidth selection procedure	CCT	CCT
# of observations	261	261

Notes: Metropolitan provinces included in the estimations are Istanbul, Ankara, Izmir, Kocaeli, Bursa, Konya, Antalya, Adana, Gaziantep, and Mersin. Managerial and professional occupations are those with ISCO-08 occupation codes starting with 1, and 2. ISCO codes starting with 1 indicate employment in managerial positions, and 2 indicate employment in professional occupations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. CCT refers to the optimal bandwidth selection estimation procedures developed by Calonico et al. (2014, 2017). Robust bias-corrected standard errors (and the associated p-values) are reported in parentheses. Optimal bandwidths are calculated by the minimization of mean-squared errors.